OPTIMAL DISPATCH OF ELECTRIC VEHICLES PERFORMING VEHICLE-TO-GRID

BY

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This work is dedicated to my loving parents and my wonderful fiancé without whom after god's help this work wouldn't have been possible.

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LIST OF ABBREVIATIONS

ADE	:	Absolute Difference Error
BW	:	Bandwidth
EDE	:	Energy Difference Error
EV	:	Electric Vehicle
FDE	:	Fair Dispatch Error
FF	:	Fairness Factor
MCP	**:**	Market Clearing Price
MIP	**:**	Mixed Integer Program
PEV	**:**	Plug-in Electric Vehicle
POP	:	Preferred Operating Point
SO	**:**	System Operator
SOC	:	State of Charge
V2G	:	Vehicle to Grid

LIST OF SYMBOLS

$En_{i,\,p}$: Estimated value of received energy by the *i*-th EV during period *p*.

ExD : Regulation down dispatch expectation.

ExU : Regulation up dispatch expectation.

$RegD_{i,\,p}$: Capacity of the i-th EV during time period p to service regulation down.

$RegU_{i,\,p}$: Capacity of the i-th EV during time period p to service regulation up.

$DisPer_i$: Percentage, to be met by the i-th EV, of the total aggregator's dispatch.

$DisEr_i$: Error between an EV's actual dispatch and its target up to that point in the scheduling period.

$EVDisp_i$: Actual dispatch value for the i-th EV during a scheduling period.

$RegS_p$: Regulation signal sent by the SO at time period p.

POP_p : Overall aggregated POP at time period p.

$nEV^{ON}{}_p$: Total number of EVs required to follow ER_t.

MP_i : Maximum power rating of EV *i* when it's switched on and charging.

$SwOn_{i,t}$: Binary variable representing if an EV has switched on (OFF to ON).

$SwOff_{i,t}$: Binary variable representing if an EV has switched off (ON to OFF).

S : Weighting constant associated with switching.

F : Weighting constant associated with fairness.

$EV_{i,t}$: Charging state of i-th EV at time t. (binary decision variable representing 0 if not charging, 1 if yes).

$FDE_{i,t}$: Error in fairness of dispatch of the i-th EV at time t.

$FDE2_{i,t}$: Error in fairness of dispatch of the i-th EV at time t using 2nd formulation.

dt : Time step size.

$DisSig_t$: Discretized signal containing the combined effect of the POP and the regulation signals.

$SOC_{i,t}$: State of charge of the i-th EV at time t.

SOC^{min} : Minimum acceptable state of charge limit on all EVs.

SOC^{max} : Maximum acceptable state of charge limit on all EVs.

$CE_{i,t}$: Energy consumed during commute trip of the i-th EV at time t.

Av_t : Set of EVs available for dispatching at time t.

nEV : Total number of available EVs.

IncDisO : Original incremental dispatch signal.

IncDis : Corrected incremental dispatch signal.

IncDis2 : Corrected incremental dispatch signal of the 2nd formulation.

ABSTRACT

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For the sake of achieving environmental sustainability and energy security, a wave of electrification is being pursued in the transportation sector to impact the environment positively. Switching to electric vehicles (EVs) is expected to greatly enhance the energy efficiency of transportation and reduce the emission impact per vehicle tremendously. Through vehicle-to-grid (V2G), EVs can also provide valuable services to the grid. To take full advantage of those services, aggregators essentially need to schedule large groups of EVs and dispatch them while abiding by the market rules. Many studies have been made focusing on aggregator scheduling algorithms while few on actual dispatch algorithms. Incremental dispatch, which is the commonly assumed technique, faces several challenges, such as high overhead communications requirements and increasing charging station costs. This work aims to overcome those obstacles by developing an optimal dispatch algorithm for EVs performing unidirectional regulation in a discrete manner. This algorithm switches EVs on and off in order to meet the system regulation signal. It also facilitates significant reductions in the required communications bandwidth and infrastructure costs. Simulations are performed on a system consisting of 1000 EVs in the PJM electricity market using high resolution regulation signals over a 24 hour period. The objectives are to evaluate the performance of this dispatch algorithm compared to the incremental dispatch algorithm and another benchmark algorithm based on priority list building. Comparison results demonstrate the superiority of the proposed algorithm in terms of reduction of required communication bandwidth and fairness to EVs participating in the V2G program.

ملخص الرسالة

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من أجل تحقيق الاستدامة البيئية و الحفاظ على أمن الطاقة ، يُجري متابعة موجة من الكهربة في قطاع النقل للتأثير على البيئة بشكل إيجابي. التحول إلى السيارات الكهربائية (المركبات الكهربائية) يُتوقع أن يعزز إلى حد كبير كفاءة استخدام الطاقة في النقل والحد من تأثير الانبعاثات لكل مركبة بشكل كبير. من خلال تقنية مركبة الى شبكة (V2G)، يمكن للسيارات الكهربائية ان توفر أيضا خدمات قيمة للشبكة. للاستفادة الكاملة من هذه الخدمات، يحتاج المحصلون/المجمعون لِجَدوَلَة مجموعات كبيرة من المركبات الكهربائية والتحكم في شحنهم مع الالتزام بقواعد السوق. تم إجراء العديد من الدراسات التي تركز على خوارزميات الجدولة في حين أن الخوارزميات التي تتحكم في عملية الشحن الفعلية أقل نسبيا. الإرسال التدريجي هو أسلوب شائع ويستخدم عادةً، ومع ذلك فإنه يواجه بعض التحديات مثل متطلبات الاتصالات العامة الخاصة به عالية والاحتياج لزيادة تكاليف المحطة. ويهدف هذا العمل المقدم للتغلب على تلك العقبات من خلال تطوير خوارزمية الإرسال والتحكم في شحن المركبات الكهربائية عن طريق تبني نظام شحن أحادي الاتجاه وبطريقة متقطّعة. ان هذه الخوارزمية تحول حالة المركبات الكهربائية ما بين يعمل ولا يعمل من أجل تلبية إشارة تنظيم الشكبكة الكهربائة المرسلة من قِبَل مدير الشبكة . ومن شأنها أيضا أن تحرز تخفيضات كبيرة في تكاليف الاتصالات اللاسلكية والبنية التحتية اللازمة. أجريت عمليات محاكاة على نظام يتألف من 1000 مركبة كهربائية في سوق الكهرباء PJM باستخدام إشارات تنظيم عالية الدقة خلال فترة 24 ساعة. وكانت الأهداف تقييم أداء هذه الخوارزمية إمقارنة بالخوارزميات السابقة. تتمثل الأهداف هذا العمل في تقييم أداء هذه الخوارزمية بالمقارنة مع خوارزميات الارسال المستمرة و مع خوارزمية مرجعية أخرى تعمل على أسس بناء قوائم الأولويات. تظهر نتائج المقارنة تفوق الخوارزمية المقترحة في مجال الحد من عرض النطاق الاتصال الترددي المطلوب، مع الالتزام بتحقيق العدل في شحن المركبات الكهربائية المشاركة في برنامج الـV2G.

CHAPTER 1

INTRODUCTION

1.1 Background

Due to concerns regarding energy security and environmental sustainability, the world has been rethinking the way energy is generated and consumed in all of its forms. The electrical sector as a result is experiencing a huge transformation. On the generation side, worldwide adoption of sustainable energy resources has been drastically increasing. The amount of renewable energy sources (RES) in the energy grid is growing. In Europe and the US, for instance, massive targets for wind power have been set [1], [2]. On the other hand, a lot of efforts on the consumption side were directed towards achieving optimal utilization of resources by making electric loads, such as motors, heaters, and appliances, more responsive and more energy-efficient.

One of the most energy demanding sectors and the one most dependent on fossil fuels is the transportation sector. More than one quarter of the energy consumption in the US is used for transportation [3]. As a result, this sector is also experiencing a wave of electrification for the sake of achieving environmental sustainability and energy security. This movement will impact the environment positively. Switching to electric vehicles (EVs) is expected to greatly enhance the energy efficiency of transportation and reduce the emission impact per vehicle tremendously. This movement, however, can cause extra burdens on existing electricity grids as they are already stressed. As a result, solutions have been proposed such as provision of Vehicle-to-grid (V2G) services. They can potentially alleviate the adverse impacts of electric vehicles (EV) on the grid and provide other benefits to the grid, hence called services. These services can also encourage increasing the adoption rate of these vehicles.

1.2 Motivation

It has been shown that electric vehicles can facilitate the integration of higher penetration of RES when their charging is coordinated properly [4]. However, EV adoption has its own limitations and by no means a straightforward process. Currently, EVs are often more expensive than conventional vehicles in their equivalent tiers and, unfortunately, public charging is still not mature. Moreover, charging EVs can result in additional burden felt by the energy grids, in many cases already stressed, if not done properly. Therefore, the need arises for developing effective techniques to integrate EVs into the energy grid such that their impact on the grid is mitigated and use of their additional load as a flexible responsive demand is made.

Vehicle-to-grid (V2G) is one proposed technique for facilitating the integration of large numbers of electric vehicles into the system. It's defined as the provision of energy and ancillary services from an EV to the electric grid [5], [6]. It promises to convert EVs into distributed energy resources from hypothetically being problematic loads. It can also hold substantial benefits to EV owners and enable them to generate value as well as supporting the grids they are connected to. EVs capable of V2G provision can offer many services to the utility grid. Such services include frequency regulation, peak shaving and responsive reserves (spinning and non-spinning) [5], [6].

Clearly a single EV can't participate in wholesale energy markets because it doesn't have the adequate capacity to do so. Aggregators therefore accumulate capacities of many EVs [9], [12]. These aggregators can be utilities controlling EVs in their distribution systems or third parties operating power plants virtually. Aggregators behave as regular market participants. They bid their aggregated EV capacities into the appropriate markets. It has been shown in previous works that the most valuable service that can be offered by EVs is often frequency regulation [10]. It depends on the market design, though [11].

There are essentially two types of V2G, unidirectional and bidirectional power flow. Unidirectional vehicle to grid is chiefly attractive since it requires almost no additional infrastructure other than the overhead communication link between the aggregators and the EVs under their control. The aggregator bids the combined capacities of several EVs into appropriate energy markets and then dispatches the individual EVs to meet dispatch signals received from the grid operator. Bidirectional V2G, on the other hand, can face strict challenges for its adoption. First of all, additional hardware is required, often not included in EVs produced currently or in the near future, in order to pump energy back into the grid. Also, issues, such as interconnection issues, anti-islanding, and protection, must be addressed. However, full bidirectional V2G can provide benefits that full unidirectional V2G cannot since the latter has limitations such as decreased power levels and reduced participation times when EVs are charging. It has been shown in [10] that these restrictions have the potential to reduce profits to less than a quarter of what could've been achieved using bidirectional V2G. Studies have shown however that in certain markets, unidirectional regulation can be more profitable due to its reduced capital costs [10].

There have been recent studies on scheduling optimization algorithms in V2G context from the aggregator's perspective[19]-[22]. Such studies primarily focus on determining how much regulation capacity to bid or schedule and on finding the most profitable times for that. As far as dispatch algorithms are concerned, most of them relied on incremental changes (increase or decrease) in the charging rates of EVs like the ones developed in [21]-[22]. This method has one major issue that is it's more expensive to build charging stations that are capable of incremental power changes than simpler charging stations. That is mainly due to the fact that they must have additional hardware to modulate their charge rate as well as communications which do not come standard [23]. Another problem is that for every new dispatch level, a new signal is required to be sent through overhead communication to every EV participating in V2G. Moreover, these signal would have high resolution since each incremental signal is a real number representing charge rate (power/ percentage of maximum charger rating of an EV). Similar incremental dispatch methods were used in [13]-[18]. While they demonstrated that EVs could respond to dispatch signals in the required time, they all suffer from the same problem of potentially utilizing high bandwidth of overhead communications since every new dispatch requires sending a new signal for each EV. In [24], a simple dispatch algorithm was introduced to address these issues. It was based on priority list building and used discrete dispatch instead of incremental. It relied on heuristics and could not always guarantee fairness in charging or optimality in the dispatch. After determining the dispatch percentage of each EV, priority lists are created for EVs' that then used for dispatch. Each EV's priority is determined based on the expected value of energy received which was computed from the scheduling algorithm. Also the algorithm was not extensively tested.

1.3 V2G Regulation Overview

V2G services can be classified into two fundamental types, namely unidirectional and bidirectional power flow. Unidirectional V2G has the advantage of requiring little additional infrastructure like the communication between an aggregator and the vehicles. On the other hand, bidirectional V2G can face serious challenges for its adoption since it would require additional hardware, often not included in current EVs or in the near future, to inject energy back into the grid. It must also address other difficulties such as dealing with interconnection issues, anti-islanding, and protection. However, bidirectional V2G can provide benefits that unidirectional V2G cannot. Unidirectional V2G limitations are related to less participation times due to only charging EV batteries, having overall decreased power levels and the potential to reduce profits to less than a quarter of what could've been potentially achieved using bidirectional V2G as was shown in [21]. Unidirectional V2G regulation can be more profitable, however, in certain markets due to its reduced capital costs [21].

A single EV undoubtedly can't participate in wholesale energy markets since it doesn't have enough capacity to do so. Aggregators, such as utilities managing EVs on their distribution systems or third parties operating virtual power plants, behave as regular market participants and therefore combine capacities of many EVs together [20], [23]. This work is thus related to a stage where the aggregator is assumed to have already signed contracts with a large fleet of EVs which allows it to manage the charging of each EV. The way aggregators make profits is by providing ancillary services to the electricity markets. Figure 1 summarizes the general steps that often occur in such markets.

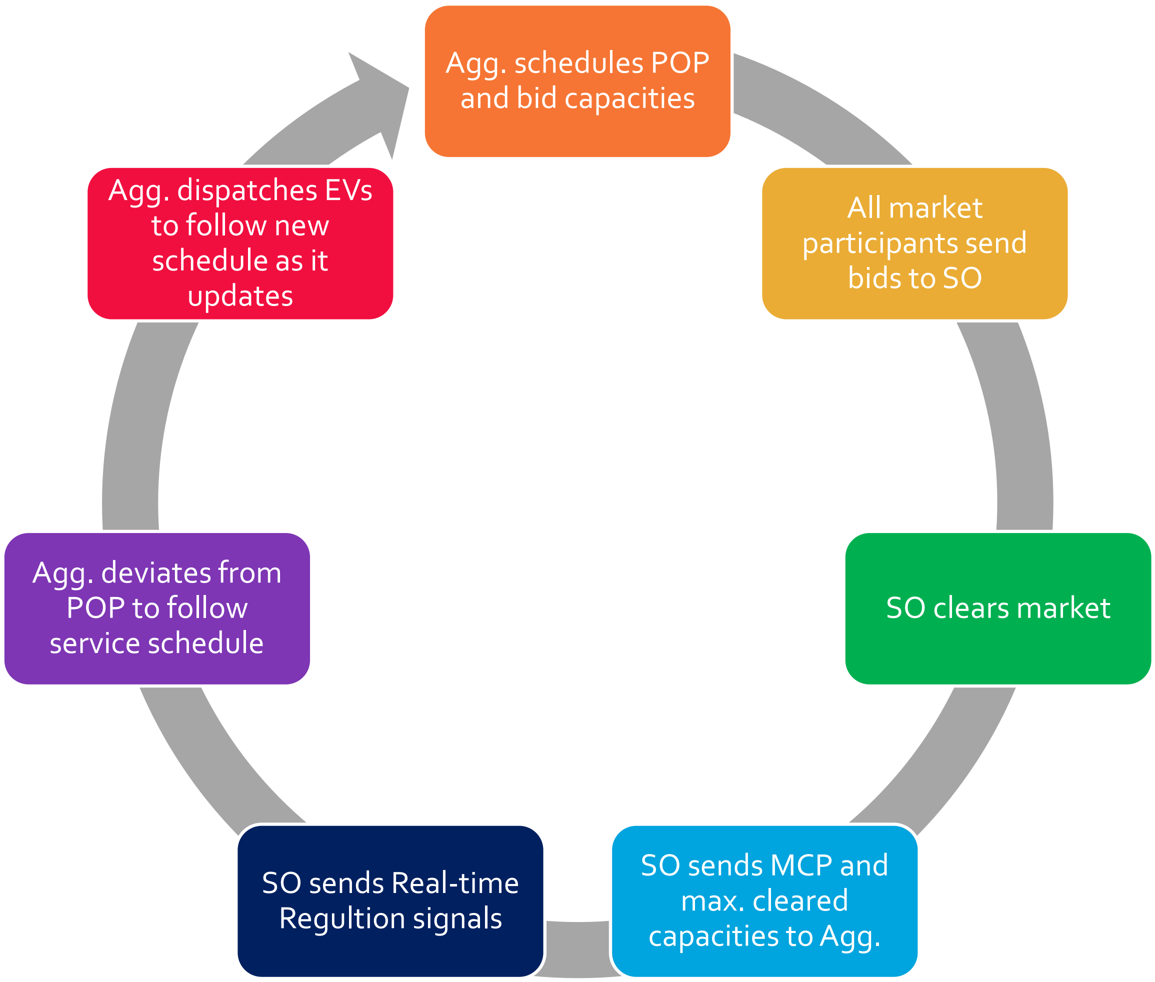

Figure 1. 1 Steps Aggregator takes to participate in regulation markets.

The general procedure in such markets, as seen in figure 1.1, is that the aggregator determines the most profitable times and how much regulation capacity to schedule using algorithms like [19]-[22]. Thus it schedules for each EV a charging rate called the preferred operating point (POP) and accordingly decide on the available reserve and regulation capacity it could provide to the markets. Similarly all market participants submit their bids for that specific period to the system/market operator (SO) ahead of time like a day ahead. The SO runs a market clearing mechanism for a specified time (e.g. an hour of the day) and determines the winning participants. The SO sends the market clearing price and cleared capacities to the aggregator (and winning participants). In real time, the SO will send to the aggregator regulation signals. The aggregator then needs to deviate from its overall POP to match the regulation service signal sent by the SO. It's up to the aggregator, however, to decide on how to execute (dispatch EVs) that command when the ancillary regulation service is to be provided. A simple and intuitive option would be to regulate the charging rate of all the charging EVs proportionally with the command signal, i.e. incremental dispatch on all EVs. As noted earlier, this option is inefficient since it requires the aggregator to send dispatch signals to each single EV being charged. Moreover, this signal would need updating at a very high dispatch rate like once every 4 seconds. This process clearly requires a large communication bandwidth and the EV charger needs to be capable of regulating its charging rate continuously. Thus the work that will be presented proposes a novel model based on optimizing discrete unidirectional dispatch. The whole process (Fig. 1) repeats for each different market period of the day, such as for a specific hour.

1.4 Problem Description

Electric vehicles (EVs) can potentially provide valuable services to utility grids through V2G technology. Aggregators are required to schedule and dispatch large numbers of EVs in order to take full advantage of V2G services. The scheduling should be executed while following market rules. While many studies looking at aggregator scheduling algorithms have been conducted in the literature, little work has been done on actual dispatch algorithms. An EV adjusts its charging rate in small increments instead of just turning on and off when using incremental dispatch schemes. The challenges faced in commonly used techniques relying on incremental dispatch are related to having high communications overhead.

This work is related to a stage where the aggregator is assumed to have already signed contracts with a large fleet of EVs which allows it to manage the charging of each EV. The way aggregators make profits is through ancillary services provision to the electricity markets. The general procedure in these markets is that each participant is required to send its offers ahead of time. The system or market operator collects all bids and offers from all participants and runs a market clearing mechanism which determines the market clearing price (MCP) and the market clearing quantity to be traded. Each winning market participant receives their cleared MCP and the maximum amount of MW they are expected to provide once it is called upon. The system operator will send ancillary service signals to the winning participants, in real-time or whenever needed, to which each participant must respond by following them. This can be done simply by increasing or decreasing consumption/generation.

Based on the expected availability of EVs and their characteristics, an aggregator constructs its bids in the day-ahead market. They schedule for each EV a charging rate called the preferred operating point (POP). The aggregator accordingly decides on the available reserve and regulation capacity it can provide to the markets. The aggregator will have to deviate from his scheduled POP for at least some of its EVs in order to follow the real-time command signal that the system operator will send. However, it is up to the aggregator to decide on how to execute that command (i.e. dispatch EVs) when the ancillary service is provided. A trivial solution would be to regulate the charging rate of all the EVs being charged proportionally with the command signal, which is referred to as incremental dispatch. This option requires the aggregator to send a dispatch signal to each single EV being charged. Moreover, this signal would need updating at a very high dispatch rate, e.g. once every 4 seconds. This process clearly requires a large communication bandwidth and the EV charger needs to be capable of regulating its charging rate continuously. The other option would be to dispatch only a subset of the EVs to reduce the bandwidth requirements while meeting the aggregator's obligations.

A new algorithm for optimal dispatch of EV fleets performing V2G services is developed in this work. The objective of this method indirectly minimizes the aggregator communication costs by keeping the number of dispatch signals needed to be sent at minimum. Aspects like ensuring charging fairness amongst the EVs were considered.

The optimal solution is need to operate very quickly since dispatch decisions need to be made typically within 4 to 10 seconds. Consequently, the new optimization algorithm will run at real-time, i.e. real-time optimization. Extensive testing was performed to verify the efficacy of the new dispatch algorithm at improving the performance in the metrics of cost, fairness and charging efficiency.

1.5 Thesis Objectives

The objectives of this work are as follows:

- To propose an optimal dispatch formulation for unidirectional V2G that minimizes switching while maintaining fairness in dispatch with respect to schedule.

- To test the proposed V2G dispatch algorithm on a power system with realistic conditions.
- Evaluate the optimal model's performance against current benchmark heuristic model

CHAPTER 2

LITERATURE REVIEW

Researching around V2G has been booming recently. This is mostly due to its great potential as a resource for stabilizing the grid and its ability to help make EV adoption more appealing. The majority of this work has focused on optimization of EV schedules in the markets and the aspects around it. Paper [30] investigated the benefits of coordinated bidding of ancillary services for unidirectional V2G while considering market uncertainties modeled using fuzzy sets. An optimal EVs charging sequence for selling regulation was formulated in [19]. This formulation assumed that charging periods are decoupled from periods of performing regulation. This meant that when performing regulation, the aggregator's preferred operating point (POP) is always zero. While performing regulation, the issue of dispatching the EVs was not addressed. The work in [20] formulated smart charging optimization without V2G and optimized V2G with only regulation. This formulation considered incremental dispatch and was for a single EV case. An optimal scheduling algorithm is considered in [25] for an entire fleet of EVs. Stochastic programming was used in this technique and it reflected bidirectional V2G of energy along with ancillary services. This method again didn't propose any particular dispatch algorithm although it considered energy that will be transferred to EVs through dispatch of the services. The work in [31] proposed a closed-form solution with the aim of optimally scheduling time-shiftable loads with uncertainties in their deadlines. It primarily focused on charging EVs with uncertain departure times and showed that significant changes in the analysis can be observed when optimizing the charging schedule of the EVs with uncertain deadlines.

Previous work in [13] and [14] showed that system regulation signals can be followed using dispatched EVs. When acting as intelligent storage, EVs can provide fast and accurate responses that would be particularly helpful for applications like spinning reserves and frequency regulation. Simulations in [15]-[17] have shown that this advantage effectively aids when integrated with wind and solar power. These approaches were also based on an incremental dispatch method and not in the structure of optimal scheduling. In an incremental dispatch scheme, an EV adjusts its charge rate in small increments instead of just turning on and off. While this method can be very accurate when matching the scheduled signal, every time a new dispatch signal is received it would unfortunately require sending a new signal to each and every EV. Such signals are typically received every 4 seconds (more or less). For large EV fleets, a large communication burden would occur as a result. An aggregator performing unidirectional regulation of EV fleet dispatch was considered in [7] and expanded in [22] to include spinning reserves. Both of these papers established incremental dispatch methods in the context of optimal schedules which also depended on continuously adjusting the charging level of each EV. In [21], a bidirectional dispatch method also based on incremental dispatch was developed for optimal scheduling.

As mentioned above a signal must be sent to every EV at every dispatch when an aggregator uses incremental dispatch. Unfortunately many EVs don't have the capability to vary their charge rates. They do, however, have the ability to remotely start and stop charging. This makes implanting a discrete dispatch method more appealing. This method although simple and guarantees fairness, it can use, however, over 90% more communications bandwidth than simple discrete dispatch methods as was shown in [24].

Almost no EV dispatch optimization, up to our best knowledge, has been ever reported in the literature in the context of ancillary services. There are some potential gains that can be made through optimally dispatching EVs performing regulation and reserves services, as was shown in[24]. If EVs are charged more efficiently, additional savings in the communications bandwidth requirements can be achieved. The reason is that there is a certain fixed amount of losses and an incremental amount of losses when charging EVs. To elaborate, charging EVs at very low rates, like at less than 2 kW, can significantly lower the charging efficiency when compared to greater than 2 kW [26].

In [27], an optimal charge control algorithm for EVs at charging stations was developed. It focused on minimizing the total charging costs of all vehicles available at the stations. Although the developed model is in the bidirectional power flow scheme and takes into consideration the varying prices of electricity throughout the day, it doesn't consider the context of performing ancillary services. The goal of this optimization was to reduce electricity costs for the whole station.

The proposed non-iterative algorithms in [28] schedules a single EV at a time once it connects to the grid. It considers implementing the discrete charging scenario in a decentralized fashion. It aims to make it suitable for real-time implementation by utilizing low-speed communication capabilities. The coordinated charging happened at a fixed rate and was considered as an uninterruptible procedure expressed in the context of solving scheduling problems. However, the developed models perform the scheduling process on the EVs sequentially. For the first model, the current aggregated load profile has to be initially sent by the system operator and wait for the EV response to update their corresponding data. This mechanism sequentially serves all EVs and consequently taking two communication signals from and back to the operator. There is a high probability that many EVs can be connected to the grid at the same time in cases of high penetration. A possible downside of that algorithm could consequently be the waiting periods for EVs that are connected simultaneously. The number of communication signal will always be double (fixed with no flexibility) the number of EVs which can potentially be a drawback or an advantage depending on the system and the size of the EV fleet. It also assumes that EVs can solve part of the optimization problem which is an extra capability that EVs would need to have.

The proposed enhanced algorithm in [28] expresses a new updating procedure performed by the grid operator for the aggregated profile. It’s based on grouping several EVs and sending their profiles once to the operator which will schedule them. Then only can the next group of EVs be processed. Thus minimizing the communication bandwidth (still at least greater than number of available EVs) and increasing the speed.

The main focus of [28] was to provide a valley filling schedule for typical peak-valley daily residential profiles and not to provide ancillary services like regulation or reserves. Even though it offered a regionalized user-focused approach designed while considering the desired outcomes of the SO in terms of minimizing the peak and variance of the aggregated load profile, it didn't concentrate on the aggregator's perspective. Moreover, scheduling EVs sequentially with an interruptible fashion could suffer from less flexibility for later scheduled EVs.

Reference [29] puts forward a regionalized approach for management of PEVs' charging. In this packetized approach, charging PEVs requests is approved for time-limited periods. This technique was reformed from approaches that handled BW sharing in communication networks. It ensured simultaneous satisfaction of distribution network constraints, maintaining relatively small communication bandwidth requirements, and fairly providing access for each vehicle to the overall available power capacity. While maintaining low complexity, the algorithm reaches suboptimal travel cost performance communication requirements while providing all vehicles with equal access to constrained resources. The developed method does not require vehicles to report or record driving their patterns. This substantially provides benefits over other approaches by protecting privacy and reducing computational and BW requirements. The algorithm treated vehicle charging problem as a random access one where charge is supplied through many "charge-packets". Without overloading the network, the "packetization" of charge efficiently used available resources and met customer objectives of reducing travel costs. Leveraging this approach, this paper reserves users' privacy more than several existing charge management structures. Similar to [28], it applies for load curve valley filling applications, but it did not take into account providing regulation and reserve ancillary services to the system.

A centralized scheduling system using a realistic vehicular mobility/parking patterns for EVs located at individual parking lots was proposed in [32]. Two different types of EVs were considered based on their mobility or parking patterns. This included regular and irregular EVs. This EV charging scheduling technique focuses on individual parking lots and takes into account a lifelike mobility pattern of the vehicles. The problem was expressed in the context of benefiting smart cities and didn't focus on providing ancillary services to the grid, however.

Some other recent work provided coordinated charging schemes but for various applications other than providing ancillary services to the system such as [33]. It proposed a two-step technique for scheduling vehicles to limit the burden on transmission and distribution assets while meeting all charging requirements. The number of EVs to be dispatched was optimized hourly based on day-ahead charging requests. The largest number of EVs that can be charged during the next hour was then determined based on operating conditions. Such conditions were to guarantee meeting the distribution reliability requirements. Reference [34], on the other hand, proposed a novel demand response management model that integrates PEVs and renewable distributed generators for future smart grids. It developed a price scheme considering fluctuation costs while bearing in mind a market where users are capable of trading the energy stored in their EVs or produced from their distributed generators. A distributed optimization algorithm was developed in which consumers' privacies were preserved as they only needed to report their aggregated loads to the utility company alone. It didn't focus on providing ancillary services to the grid.

CHAPTER 3

BENCHMARK HEURISTIC DISPATCH ALGORITHM

To the best of our knowledge, very few discrete dispatch algorithms have ever been reported in the literature in the context of ancillary services. It was shown in [24] that there are some potential gains that can be made through efficiently dispatching EVs performing regulation and reserves services. However it hasn't been applied in an optimal manner.

An intelligent dispatch algorithm was proposed in [24] with the aim of reducing the required communication costs associated with incremental dispatch algorithms. The proposed alternative approach aimed to achieve an overall response to the system regulation signal by switching the EVs on and off only (discretely). To achieve that, the regulations signal received is added to the preferred operating point (POP) of the aggregator. Then the combined signal is discretized into increments such that it's possible to follow the discretized signal by switching on individual EVs. The total number of electric vehicles needed to follow that signal depends on the power they draw when switched on. Dispatch deployment signals are then sent to the EVs changing states (from ON to OFF or vice versa).

The overall algorithm is shown in figure 3.1. For each EV, the dispatch percentage is determined first and used for calculating their dispatch priorities. The priority is set based on the expected amount of received energy that was computed using a scheduling algorithm. The scheduling algorithm also determines the hourly capacities that each EV can bid into the market. Using [21], [22], the expected energy to be received during a period p can be calculated using (3.1) below:

$$En_{i,p} = POP_{i,p} - RegU_{i,p} \cdot ExU + RegD_{i,p} \cdot ExD) \qquad (3.1)$$

where

$En_{i,p}$ is the estimated value of received energy by the i-th EV during period p.

$RegU_{i,p}$ is the capacity of the i-th EV during time period p to service regulation up.

$RegD_{i,p}$ is the capacity of the i-th EV during time period p to service regulation down.

ExU is the regulation up dispatch expectation.

ExD is the regulation down dispatch expectation.

It can be noted that the values for ExU and ExD can be estimated using the average historical hourly percentages of the dispatched capacities [21], [22].

The priority of each EV is given from its dispatch percentage and its dispatch percentage error, which depend on the expected value of received energy and are given by (3.2) and (3.3) below:

$$DisPer_{i,p} = \frac{En_{i,p}}{\sum_{i=1}^{cars} En_{i,p}} \qquad (3.2)$$

$$DisEr_{i,p} = \frac{DisPer_{i,p} - \frac{\sum_{\tau=1}^{t} EVDisp_{i,\tau}}{\sum_{i=1}^{cars}\sum_{\tau=1}^{t} EVDisp_{i,\tau}}}{DisPer_{i,p}} \qquad (3.3)$$

Where

DisPer$_i$ is the percentage, to be met by the *i*-th EV, of the total aggregator's dispatch.

DisEr$_i$ is the error between an EV's actual dispatch and its target up to that point in the scheduling period.

EVDisp$_i$ is the actual dispatch value for the *i*-th EV during a scheduling period.

The next step is to categorize the EVs, based on priority of dispatch, into two lists in order to reduce their rapid toggling while charging them. The 'turn off' list contains the *n* EVs, sorted in ascending order, needed to meet the aggregated POP and are therefore already switched on. The remaining EVs, which are off, are placed in the 'turn on' list and sorted in descending priority.

The regulation signal received from the SO is then discretized. This inherently introduces errors between the two signals. However, it has been shown in [24] these differences are negligible that for groups with many EVs. The amount of energy needed to follow the discretized signal, ER_t, given by the SO and the number of EVs required to do so are then determined. These are given by (3.4) and (3.5) below for any time instance *t*:

$$ER_p = POP_p + RegS_p \tag{3.4}$$

$$nEV_p^{ON} = \frac{ER_p}{MP} \tag{3.5}$$

Where

$RegS_p$ is the regulation signal sent by the SO at time period *p*.

POP_p is the overall aggregated POP at time period *p*.

nEV^{ON}_p is the total number of EVs required to follow ER_t.

MP is the charger rating of an EV when it's switched on.

Once the number of EVs needed to follow the deployment signal is determined, it is compared to the number of EVs available in the 'turn off' list. If the total number of EVs required to stay switched on is less than the number of vehicles in the 'turn off' list by *m*, the *m* EVs at the bottom of the list are moved to the bottom of the 'turn on' list (switched off). Whereas if the number of EVs needed is more than the number in the 'turn off' list by *m*, the top *m* EVs in the turn on list are relocated to the top of the 'turn off' list (switched on). The dispatch priorities are reevaluated after a certain number of dispatches and the lists are rebuilt based on the new priorities of dispatch at those times. The algorithm stops at the end of the scheduling period to calculate new V2G capacities determined from the scheduling algorithm.

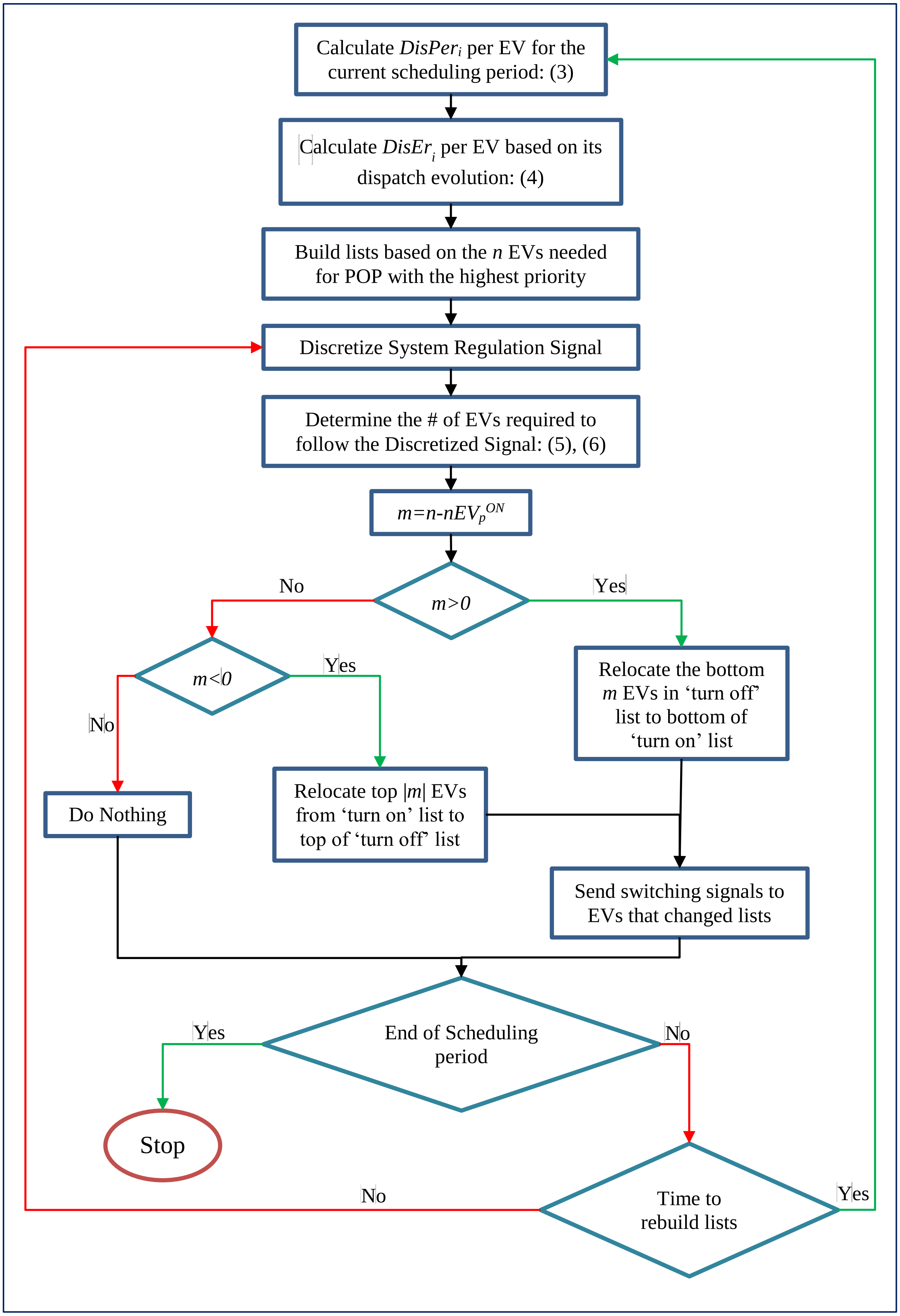

Figure 3. 1 Intelligent Dispatch Algorithm

CHAPTER 4

OPTIMAL DISPATCH ALGORITHM

4.1 Discrete Mode

4.1.1 Formulation 1: Fairness as Part of the Objective Function

The proposed algorithm in this paper will dispatch EVs in a discrete unidirectional manner. This means that the EVs will have either one of two states, ON/Charging or OFF.

To dispatch EVs in a discrete unidirectional mode, the problem can be expressed as an integer linear programming one. The decision variable will then be binary number with value of 1 if the EV is charging and 0 when it's switched off.

This problem's objective is to minimize the total number of switching instances each time a new regulation signal is received and consequently reducing the number of message signals to be sent and thus the costs associated with acquiring communication bandwidth. The algorithm thus evaluates the optimal solution in real time and the objective function along with its constraints are expressed as follows.

Minimize:

$$S \cdot \sum_{i=1}^{nEV} \left(SwOn_{i,t} + SwOff_{i,t} \right) + F \cdot \sum_{i=1}^{nEV} \left(FDE_{i,t} \right) \qquad (4.1.1)$$

Subject to:

$$SwOn_{i,t} = max(0, EV_{i,t} - EV_{i,t-1}) \qquad , \forall i \in nEV \qquad (4.1.2)$$

$$SwOff_{i,t} = ma\,x\left(0, EV_{i,t-1} - EV_{i,t}\right) \qquad , \forall i \in nEV \qquad (4.1.3)$$

$$SOC^{min} \leq SOC_{i,t} \leq SOC^{max} \qquad , \forall i \in nEV \qquad (4.1.4)$$

$$\sum_{i=1}^{nEV} EV_{i,t} \cdot MP_i = DisSig_t \qquad , \forall i \in Av_t \qquad (4.1.5)$$

$$SOC_{i,t} = SOC_{i,t-1} + EV_{i,t} \cdot MP_{i,t} \cdot dt - CE_{i,t} \qquad , \forall i \in nEV \qquad (4.1.6)$$

where

$SwOn_{i,t}$ is a binary variable representing if an EV has switched on (OFF to ON).

$SwOff_{i,t}$ is a binary variable representing if an EV has switched off (ON to OFF).

S is the weighting constant associated with switching.

F is the weighting constant associated with fairness.

$EV_{i,t}$ is the charging state of *i*-th EV at time *t.* (binary decision variable representing 0 if not charging, 1 if yes).

$FDE_{i,t}$ is the error in fairness of dispatch of the *i*-th EV at time *t.*

MP_i is the maximum power rating of the charger of the *i*-th EV

dt is the time step size.

$DisSig_t$ is the discretized signal containing the combined effect of the POP and the regulation signals.

$SOC_{i,t}$ is the state of charge of the i-th EV at time t.

SOC^{min} is the minimum acceptable state of charge limit on all EVs.

SOC^{max} is the maximum acceptable state of charge limit on all EVs.

$CE_{i,t}$ is the energy consumed during commute trip of the i-th EV at time t.

Av_t is the set of cars available for dispatching at time t.

nEV is the total number of available EVs.

The proposed model is an integer problem due to the binary nature of the decision variable EV_i. This increases the complexity of the problem as compared to simpler linear programming problems.

The objective function (4.1.1) minimizes the total number of switching instances, ON to OFF (4.1.2) and vice versa (4.1.3), and the error in fair dispatch each time a new regulation signal is received while considering the appropriate constraints. The constants S and F control the weight of switching instances and fair dispatch respectively and their values can be used to favor one over another. Throughout the analysis period, (4.1.4) ensures that the SOC of all EVs is maintained within acceptable bounds. This would help EV owners expect their cars to be charged at an acceptable level in case an unexpected event occurs and they need to use their vehicles. The state of charge of the EVs gets updated using (4.1.6). In the case of t=1, at the beginning of the analysis period, $SOC_{i,t-1}$ can be replaced with the initial or arrival state of charge of each vehicle.

Constraint (4.1.5) is to ensure that all available EVs at each time instance are dispatched to follow the received deployment signal. It's important to note that the received signal is a discretized version of the actual deployment signal Sig_t which is simply the summation of the preferred operating point of the aggregator and the received regulation signal from the SO. As the decision variable is an integer, discretizing the signal is a crucial step to ease the analysis since the overall dispatching power capacity can have discrete values (combinations of MP_i when switching individual EVs). This is a valid assumption since the introduced error from discretization can be reduced to acceptable levels when dispatching large numbers of EVs as was verified by [24].

Maintaining fairness in charging the EVs is an important feature of this model and is controlled using the value of constant F in (4.1.6). FDE is the percentage difference calculated each time with respect to the potential incremental dispatch signal as shown in (4.1.7).

$$FDE_{i,t} = \frac{|EV_{i,t} \cdot MP_{i,t} - IncDisO_{i,t}|}{IncDis_{i,t}} \quad ,\forall i \in Av_t \qquad (4.1.7)$$

Incremental dispatch can be considered the fairest way to dispatch the EVs. However, it's the least efficient it requires sending a communication message to each available EV to update its dispatch. Aggregators can control S and F to maintain a desirable balance between fairness and flexibility in dispatch which can potentially furthermore reduce the switching signals. The original incremental dispatch signal for each EV can be generally evaluated as in (4.1.8) by using the prescheduled POPs and bid capacities of each EV along with the actual received regulation signal from the system operator. In (4.1.8) the received regulation signal from the SO can be for performing an ancillary service of either regulation up or down, so the corresponding bided regulation capacity should be used.

$$IncDisO_{i,t} = POP_{i,t} + \frac{RegSig_t \cdot RegCap_{i,t}}{\sum_{i=1}^{nEV} RegCap_{i,t}} \qquad (4.1.8)$$

A slight modification has been applied to the original incremental dispatch of (4.1.8) to form a new incremental signal that would help in evaluating (4.1.7) properly. The modified signal is shown below.

$$IncDis_{i,t} = \begin{cases} 1, & IncDisO_{i,t} < 1 \\ IncDisO_{i,t}, & otherwise \end{cases} \qquad (4.1.9)$$

The idea behind (4.1.9) is that any incremental dispatch signal lower than 1W can have adverse effects on the value of *FDE* in (4.1.7). If the original incremental dispatch (4.1.8) was also used in the denominator, any positive value less than 1 would result in a very high value of *FDE* if an EV was switched ON. An incremental signal of 0 would yield the problem infeasible. Thus (4.1.9) is a valid correction. Any incremental signal larger than 1W is taken into account and the *FDE* is the percentage difference between actual dispatch and incremental dispatch as expected. Any change in power less than 1W is considered negligible, and then the *FDE* will be the absolute difference between the two signals.

Figure 4.1 below shows a sample analysis to test if the designed model would help the optimizer perform as desired under cases of different values of the incremental dispatch signal. Say that at some time instant through analysis that there are three different EVs color coded Red, Green and Blue with original incremental dispatch signals of 100W, 50W and 0.5W respectively. The maximum charger rating (*MP*) for all of them was assumed to be 3.3kW. Depending on whether the EV is switched On/Off the value of *FDE* will be different. Moreover, it will also depend on whether the value of *IncDisO* is greater than 1W or not. In this example, the value of *IncDis* will be equal to 1 for the blue EV only and unchanged for the others. Depending on the value of the discretized signal $DisSig_t$, a certain number of EVs will be needed to switch on. It can be seen that the way *FDE* is formulated makes the optimizer follow the intuitive desired outcome which is prioritize switching on EVs with higher *IncDisO* and switching off EVs with lower *IncDisO*.

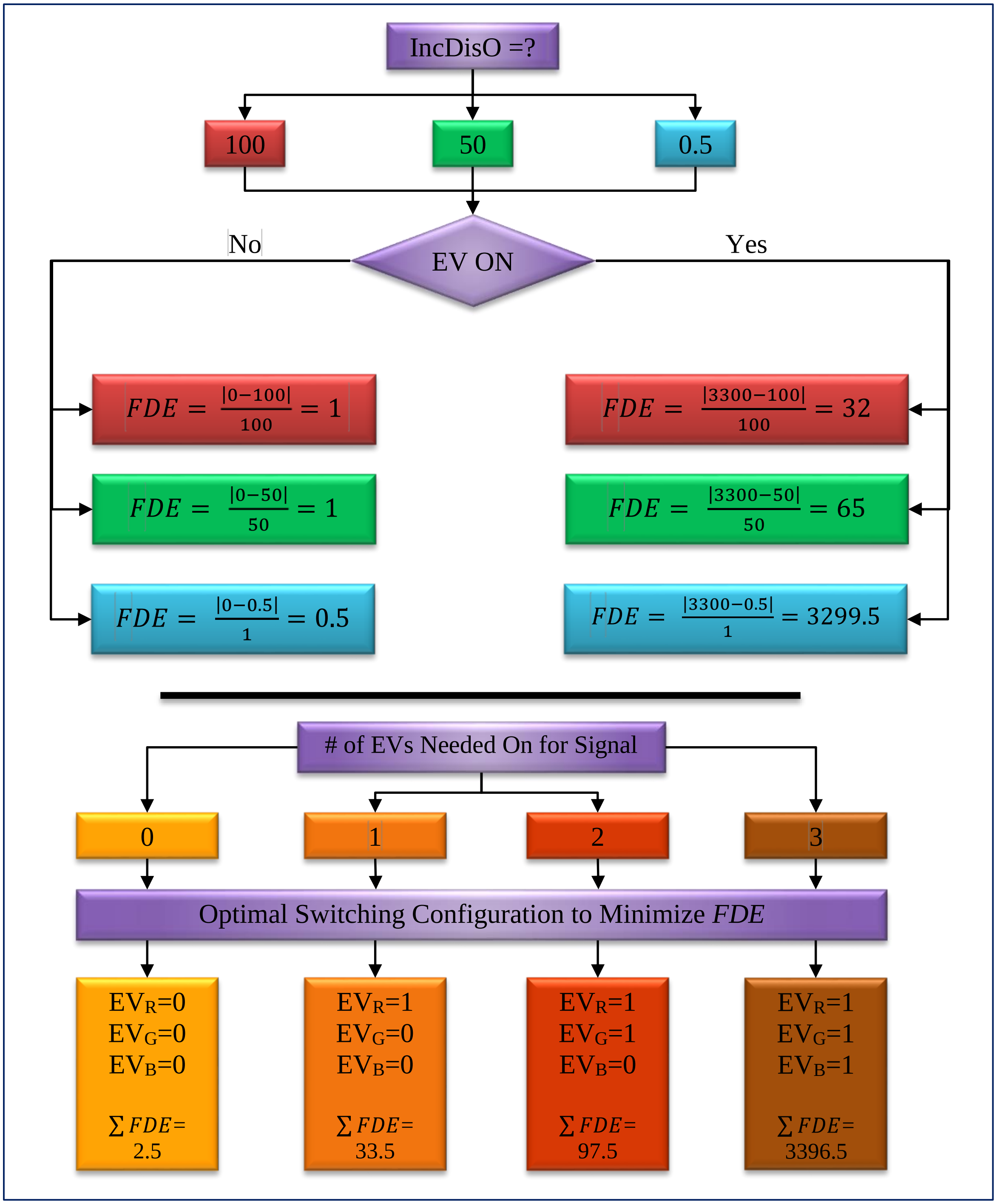

Figure 4. 1 Analysis of the of FDE in Formulation 1 Effectiveness Under Diverse Cases

4.1.2 Formulation 2: Fairness as Part of the Constraints

The problem can also be approached from another perspective and formulated as follows:

Minimize:

$$\sum_{i=1}^{nEV} \left(SwOn_{i,t} + SwOff_{i,t} \right) \tag{4.1.10}$$

Subject to:

$$SwOn_{i,t} = max(0, EV_{i,t-1} - EV_{i,t}) \quad , \forall i \in nEV \tag{4.1.11}$$

$$SwOff_{i,t} = max\left(0, EV_{i,t} - EV_{i,t-1}\right) \quad , \forall i \in nEV \tag{4.1.12}$$

$$SOC^{min} \leq SOC_{i,t} \leq SOC^{max} \quad , \forall i \in nEV \tag{4.1.13}$$

$$\sum_{i=1}^{nEV} EV_{i,t} \cdot MP_i = DisSig_t \quad , \forall i \in Av_t \tag{4.1.14}$$

$$SOC_{i,t} = SOC_{i,t-1} + EV_{i,t} \cdot MP_{i,t} \cdot dt - CL_{i,t} \quad , \forall i \in Av_t \tag{4.1.15}$$

$$FDE2_{i,t} \leq FF \quad , \forall i \in Av_t \tag{4.1.16}$$

Note that constraints (4.1.11)-(4.1.15) are the same as in the previous formulation. The main difference is in removing the fairness metric from the objective function and including it as a constraint (4.1.16). Maintaining fairness in charging the EVs is an important feature of this model and is now controlled using (4.1.16) which maintained the error in fairly dispatching each EV under a certain level (*FF*), where *FDE2* is the percentage difference calculated each time with respect to the potential incremental dispatch signal. It can be seen that using (4.1.7) to compute *FDE* would be difficult to track as a constraint since it can represent either a percentage difference or an absolute difference. Therefore a new way to evaluate the error in fair dispatch is proposed below.

$$FDE2_{i,t} = \frac{|EV_{i,t} \cdot MP_{i,t} - IncDis2_{i,t}|}{IncDis2_{i,t}} \quad ,\forall i \in Av_t \qquad (4.1.17)$$

Where *IncDis2* is the corrected version of the original incremental dispatch signal (*IncDisO*) evaluated using (4.1.18) below.

$$IncDis2_{i,t} = \begin{cases} HNum, & IncDisO_{i,t} < 1 \\ IncDisO_{i,t}, & otherwise \end{cases} \qquad (4.1.18)$$

It can be seen that this formulation makes changes if the original incremental dispatch signal has negligible values less than 1W and replaces them with a high number *HNum* and unchanged otherwise. It can be noticed that the lowest value *FF* can possibly have is 1. The reason is that when *IncDisO* is less than 1W, *FDE2* will automatically be equal to 1. Constraining *FDE2* in (4.1.16) to be less than 1 would yield the problem infeasible in the cases of *IncDisO* < 1.

One drawback of this formulation is the *FF* in (4.1.16) becomes a common limit for all EVs. Since it's a constraint, all *FDE* values should be below *FF* at a time instance where it might be required for a few EVs to exceed *FF* and can be much less for others. The 1st formulation on the other hand considered the *FDE* for each specific EV and minimized the overall sum. Thus the previous formulation provides more flexibility in dispatching each EV uniquely and controllability for the aggregator.

Another drawback of this formulation is related to *FDE2* and its dependence on IncDis2. Figure 4 below shows the same analysis performed using the 1st formulation and how under some circumstances the optimizer would select counterintuitive solutions. The same assumptions were made as in figure 4.2 with the addition of *HNum*=100000. Note that the value of *HNum* should be chosen much higher than the largest maximum charger rating amongst all EVs ($HNum >> \max(MP_i)$). It can be seen that even though this formulation avoids dividing by 0 or a number less than 1, it still has a major issue. In the cases of EVs switched off, all EVs are treated equally and the ones with lower *IncDisO* are not prioritized. Moreover, the problem becomes more severe in cases were EVs need to be switched on. The optimizer would now prioritize EVs with low or zero *IncDisO* signals which is the opposite of what's desired.

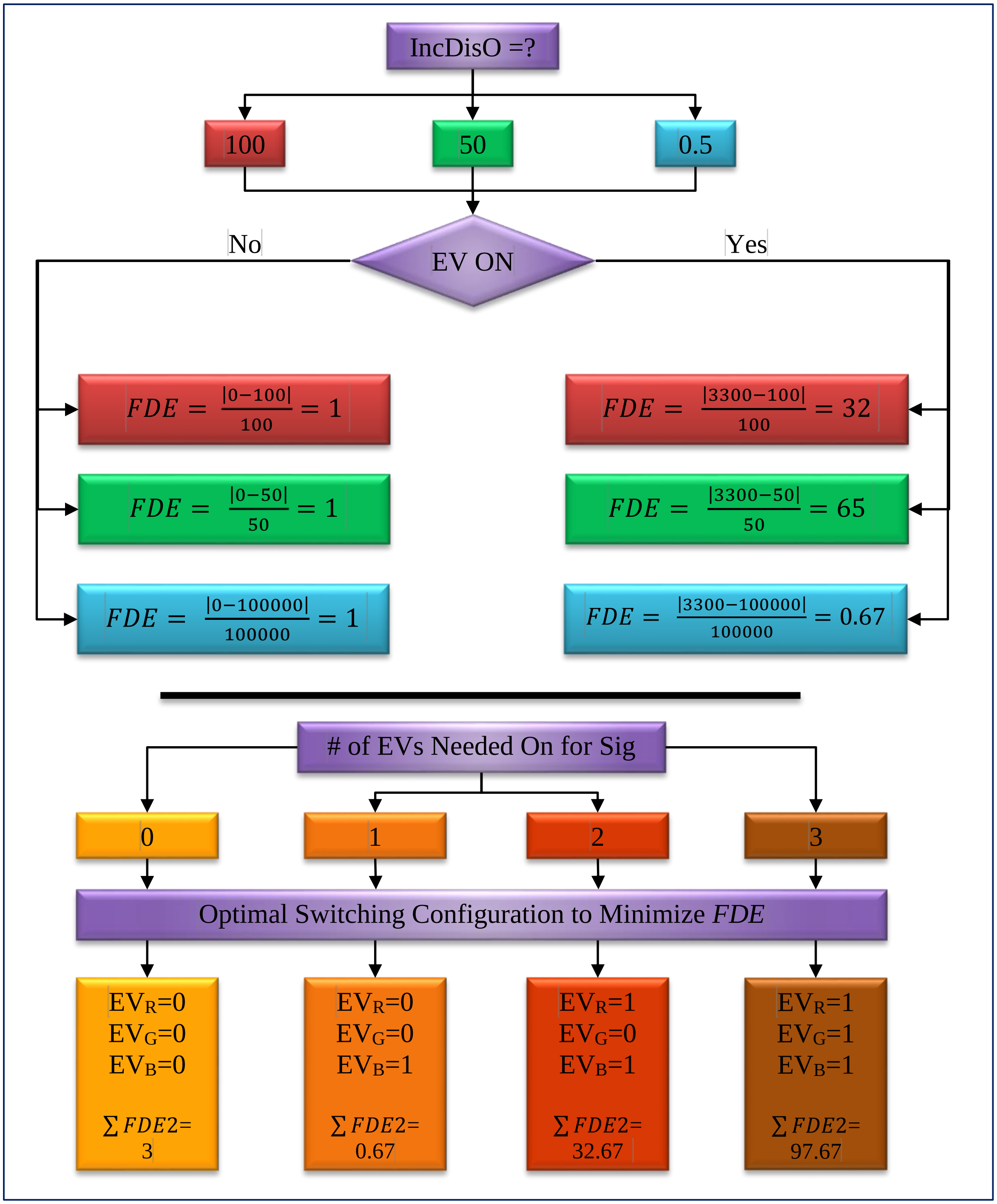

Figure 4. 2 Analysis of the of FDE in Formulation 2 Effectiveness Under Diverse Cases

4.2 Continuous Mode

This mode has the assumption that either the EV chargers have the capability of controlling their charging rate or that they're available at charging station with this capability. This means that unlike the previous case, we now can charge the EVs at various levels between zero and its maximum charging rate. Moreover, the problem now would be a linear program rather than a MIP which is often simpler to solve. The formulation will be similar to (4.1.10)-(4.1.16) with the following changes:

- The continuous mode was built based on the 2nd discrete dispatch formulation presented in section 4.1.2 before.
- (4.1.19) and (4.1.20) no longer represent switching on or off. They now represent increasing and decreasing the charging rate respectively.
- The reason is that our decision variable is no longer binary. An exact value of the deployment signal could be followed (feasible). That is the original deployment signal Sig_t will be used (4.1.25) instead of $DisSig_t$ in (4.1.14).

The problem can thus be formulated as follows:

Minimize:

$$\sum_{i=1}^{nEV}\left(IncCh_{i,t} + DecCh_{i,t}\right) \tag{4.2.19}$$

Subject to:

$$IncCh_{i,t} = max(0, EV_{i,t-1} - EV_{i,t}) \quad ,\forall i \in nEV \tag{4.2.20}$$

$$DecCh_{i,t} = ma\,x\left(0, EV_{i,t} - EV_{i,t-1}\right) \quad ,\forall i \in nEV \tag{4.2.21}$$

$$SOC^{min} \leq SOC_{i,t} \leq SOC^{max} \quad ,\forall i \in nEV \tag{4.2.22}$$

$$\sum_{i=1}^{nEV} EV_{i,t} \cdot MP_i = Sig_t \quad ,\forall i \in Av_t \tag{4.2.23}$$

$$SOC_{i,t} = SOC_{i,t-1} + EV_{i,t} \cdot MP_{i,t} \cdot dt - CL_{i,t} \quad ,\forall i \in Av_t \tag{4.2.24}$$

$$FDE2_{i,t} \leq FF \quad ,\forall i \in Av_t \tag{4.2.25}$$

$$0 \leq EV_{i,t} \leq 1 \quad ,\forall i \in Av_t \tag{4.2.26}$$

The added condition (4.2.26) indicates that our decision variable is not the state of charge of the EV (on/off). It now represents the percentage out of the maximum charger rating MP_i of the *i*-th EV charging at time *t*.

The new nature of the decision variable now raises some concerns in the continuous mode. Not only this model is now similar to incremental dispatch in terms of requiring more communication bandwidth as compared to sending binary signals, the objective function now also minimizes the change in charge rating. That means the optimizer would treat a changes in charging rates differently depending on their magnitudes. For instance, changing the charging rate of an EV by 25% and 50% is different and the optimizer would prioritize the change of 25%. In our application, however, both cases should be treated equally since a communication message would be sent to the 2 EVs anyway.

CHAPTER 5

RESULTS

5.1 Synopsis of System Parameters

5.1.1 System and EV Parameters

The proposed algorithm was tested on a system with 1000 EVs including Tesla Model S85D [36], Ford Focus Electric [37], Tesla Model 60D [36] and Nissan Leaf [38] with parameters shown in Table 1 below. Note that the maximum charging ratings were limited to 3.3kW for all cars to simplify discretizing the signal and the optimizer would consider all cars equal when assigning their respective dispatch signals.

Table 1 EV Parameters

EV Model	Battery Capacity (kWh)	Max Charger Rating (kW)	# of Cars in System
Model S 85D	85	3.3	250
Focus Electric	23	3.3	250
Model S 60D	60	3.3	200
Leaf	24	3.3	300

The simulation was done for a whole day using PJM regulation market data [35]. The signal has 2s resolution which is considered high. This means that the optimization algorithm should solve the dispatch problem relatively lower than that time. It was assumed that all vehicles were fully charged initially and the preferred SOC^{max}=100%.

Using historical data, an aggregator can determine the expected numbers of EVs available for dispatch. Figure 5.1 below shows the expected availability of EVs for dispatch by the aggregator. EVs' experience energy losses due to commute trips through the day and they're also considered unavailable to dispatch during these times. It has been assumed that EVs go for two trips daily. The first trip occurs sometime during the first 3 hours of analysis and the second is in the middle of the day. Therefore it can be observed that the expected number of EVs available to the aggregator is low during these times. These numbers however are prone to change in case some EVs became charged after reaching SOC_{max} or due to unexpected leaving/ disconnecting events.

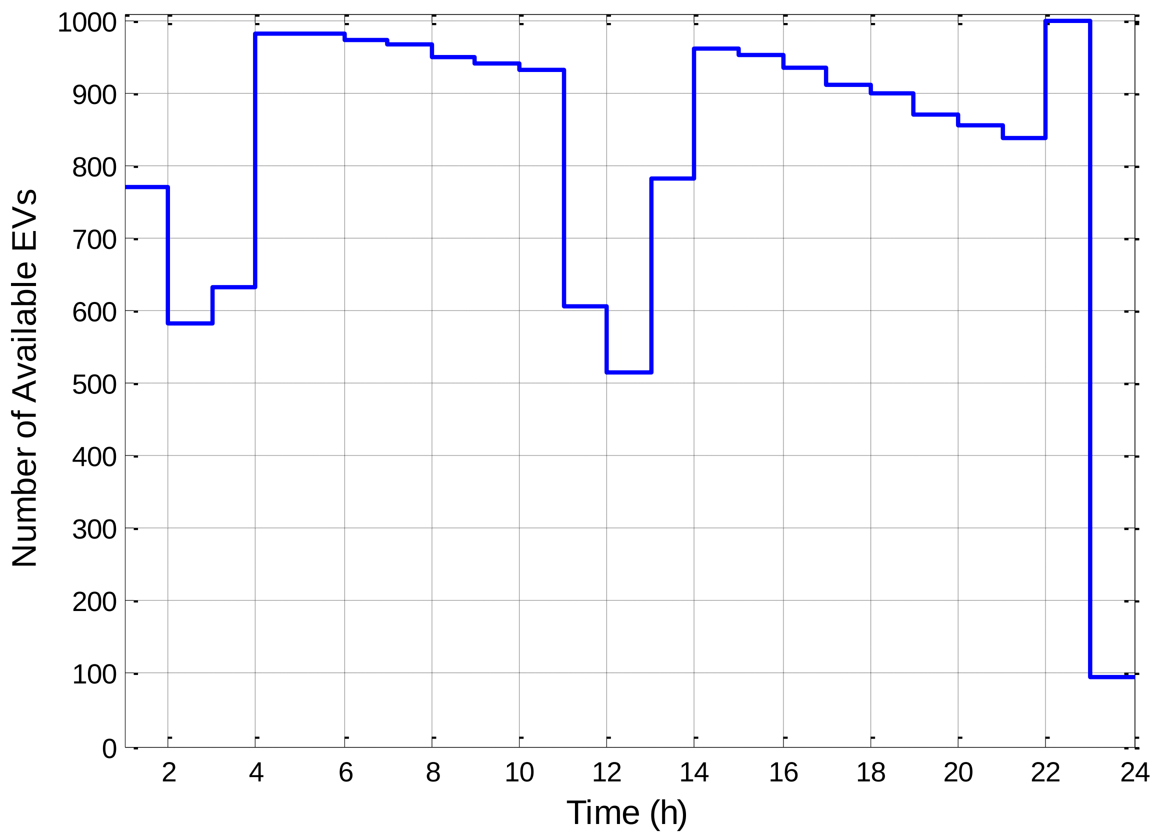

Figure 5. 1 Hourly Expected EV Availability for Dispatch throughout Analysis Period

5.1.2 System Evaluation Parameters

To analyze and evaluate the performance of the developed models, some parameters will be introduced. These parameters will later help in evaluating the performance of the proposed algorithm and compare it with the conventional one as well as showing how some aspects of the system might not necessarily indicate poor performance.

- The first parameter is the total number of communication messages sent. As mentioned earlier, the main objective of this work was to minimize the messaging traffic costs through reducing the overall communication BW requirements.
- The second parameter is related to fairness. Ultimately what we care about after minimizing switching instances is to do so while maintaining fairness with respect to incremental dispatch. Thus, the mean absolute difference error (mean *ADE*) is defined. It's the overall mean absolute difference between the actual and incremental dispatched powers (W) using any of the discussed algorithms before.
- The third parameter is also related to fairness. It's the overall mean difference in energy (Wh) per time instance between actual and incremental dispatch. That is (actual-incremental)**dt.* It gives an indication of whether on average and algorithm is dispatching more than the schedule or less. In case of unidirectional dispatch, charging more would be better in terms of charging more vehicles faster.

An extra indicator is actually not dependable for performance evaluation of a model. It's rather introduced for analysis purposes. Considering any EVs with final SOCs lower than 95% of their scheduled target from incremental dispatch, EV Violations will represent the number of EVs under that limit. The reason this indicator isn't dependable is due to the fairness requirements that need to be met. An EV can have a relatively low SOC due to several reasons such as its schedule was originally low, it had more unexpected departures than other EVs, the overall scheduled energy was not enough to charge all EVs, …

5.1.3 Computational System Parameters

The simulations were performed on a Windows 10 Pro PC with the specifications shown below:

- Processor: Intel Core i7-3630QM CPU @ 2.40 GHz.
- Installed Memory (RAM): 32.0 GB (approximately 2-3 GB were needed for simulations).
- Software used: CVX (Matlab-based modeling system for convex optimization) with professional license.
- Optimizer: Gurobi 6.0.5.

5.2 Benchmark Heuristic Dispatch Algorithm

The conventional algorithm [24] was tested on a signal developed using scheduling algorithms [21], [22]. It can be seen from figure 5.2 that the model performs as expected in terms of following the given deployment schedule.

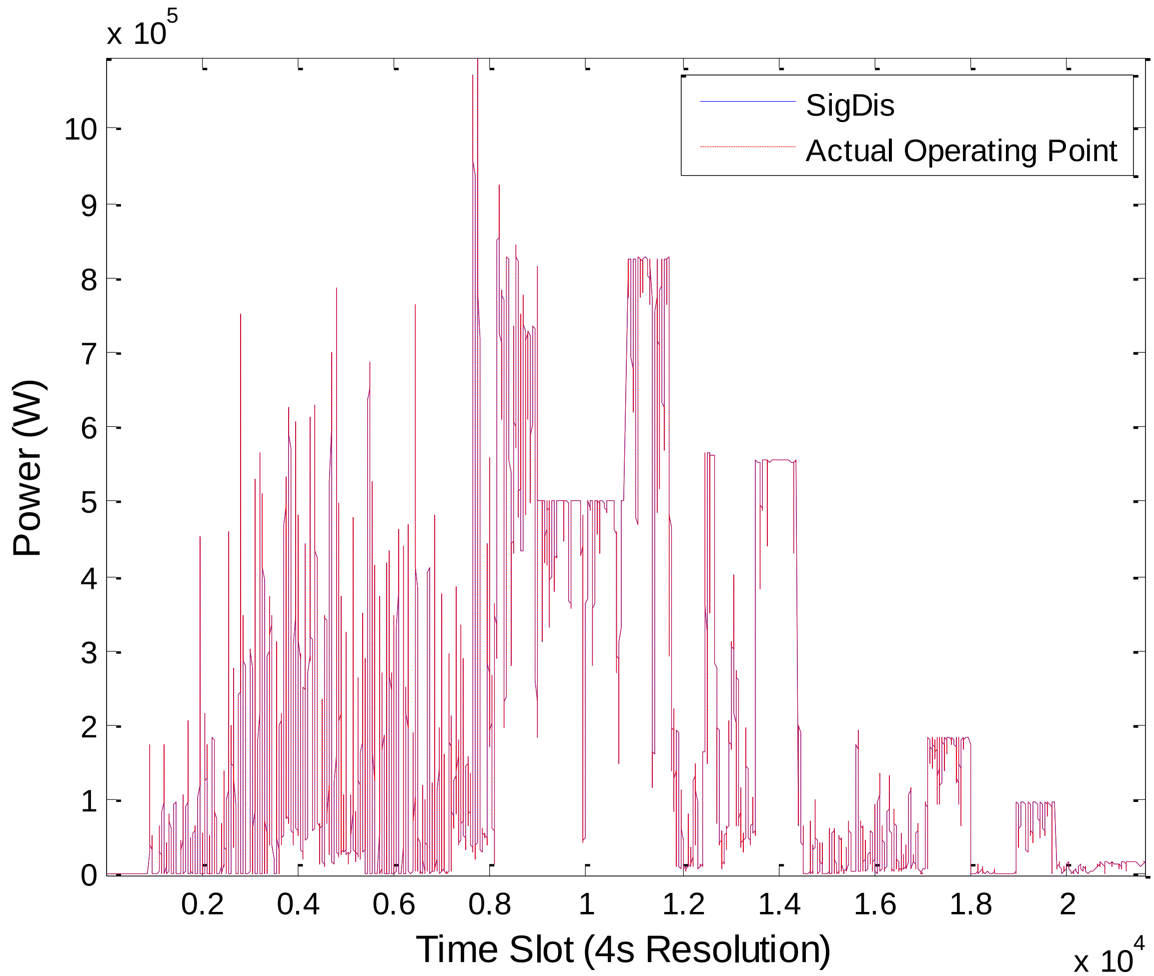

Figure 5. 2 Benchmark Heuristic Dispatch Operating Point Following Scheduled Deployment Signal

The reason the aggregator is always able to meet the schedule is that there are enough EVs available for dispatch to cover the highest signal requirements. This effect can be noticed in figure 5.3. As the EVs dispatch they get charged until they meet their SOC^{max} requirements effectively making them unavailable to the aggregator for dispatch even if they were connected to the grid. As long as the number of effectively available (blue curve) cars is larger than the number of vehicles required to meet the deployment signal, there will be no issues in following $DisSig_t$.

If the aggregator expects to have less EVs than the originally expected quantities due to any new circumstances that appear. The schedule needs to be modified accordingly.

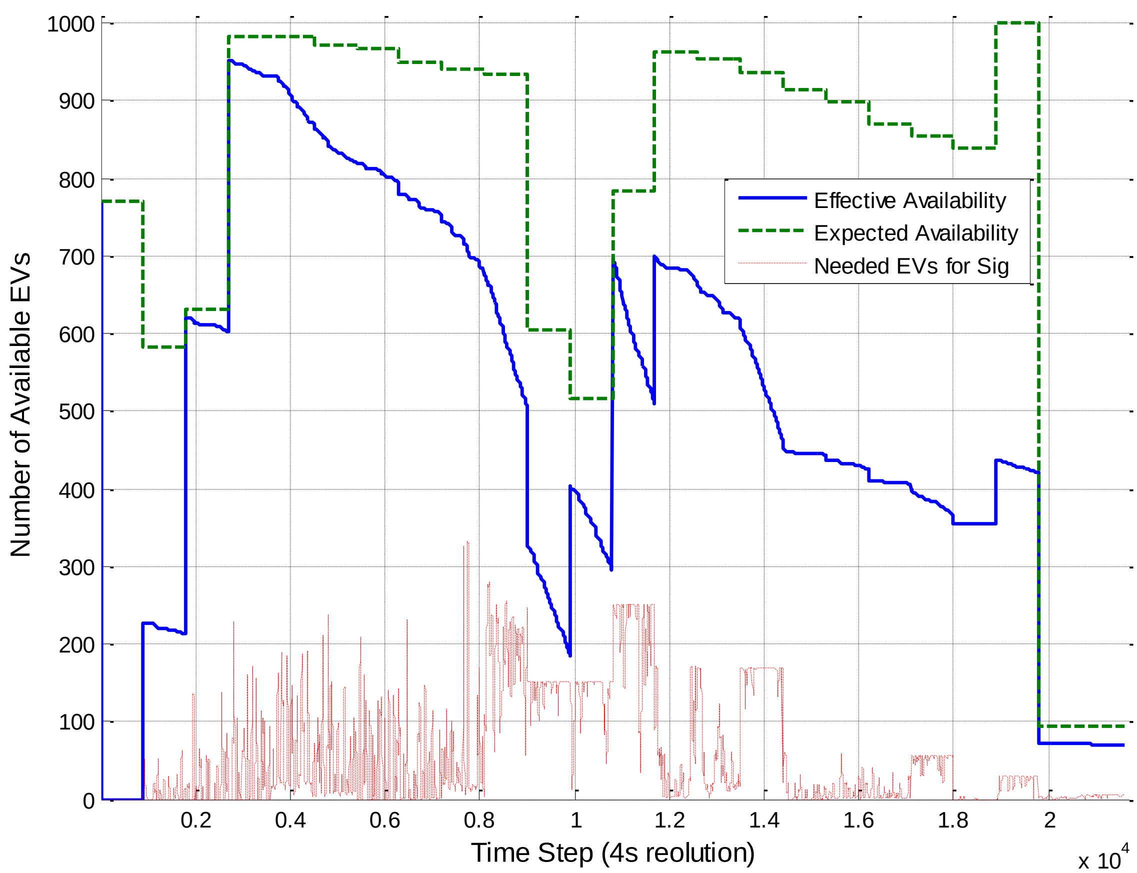

Figure 5. 3 EV Availability for Intelligent Dispatch throughout Analysis Period

Table 2 below summarizes the performance evaluation results of the conventional dispatch algorithm.

Table 2 Performance Evaluation of Intellignet Dispatch Algorithm

Total # of Messages	Overall Mean ADE (W)	Overall Mean EDE (Wh)	EV Violations
34055	327.8358	-0.0042	41

Figure 8 below shows the sorted final *SOC* profiles of all EV sorted in ascending order. The first 250 EVs are the Ford Focus Electrics, the next 300 are the Nissan leafs followed by the Tesla Model S 60D and 85D respectively. The battery capacities of all the EV types are also shown.

As far as the *ADE* is considered, figure 5.4 shows the mean ADE of all EVs during each time instance of the analysis.

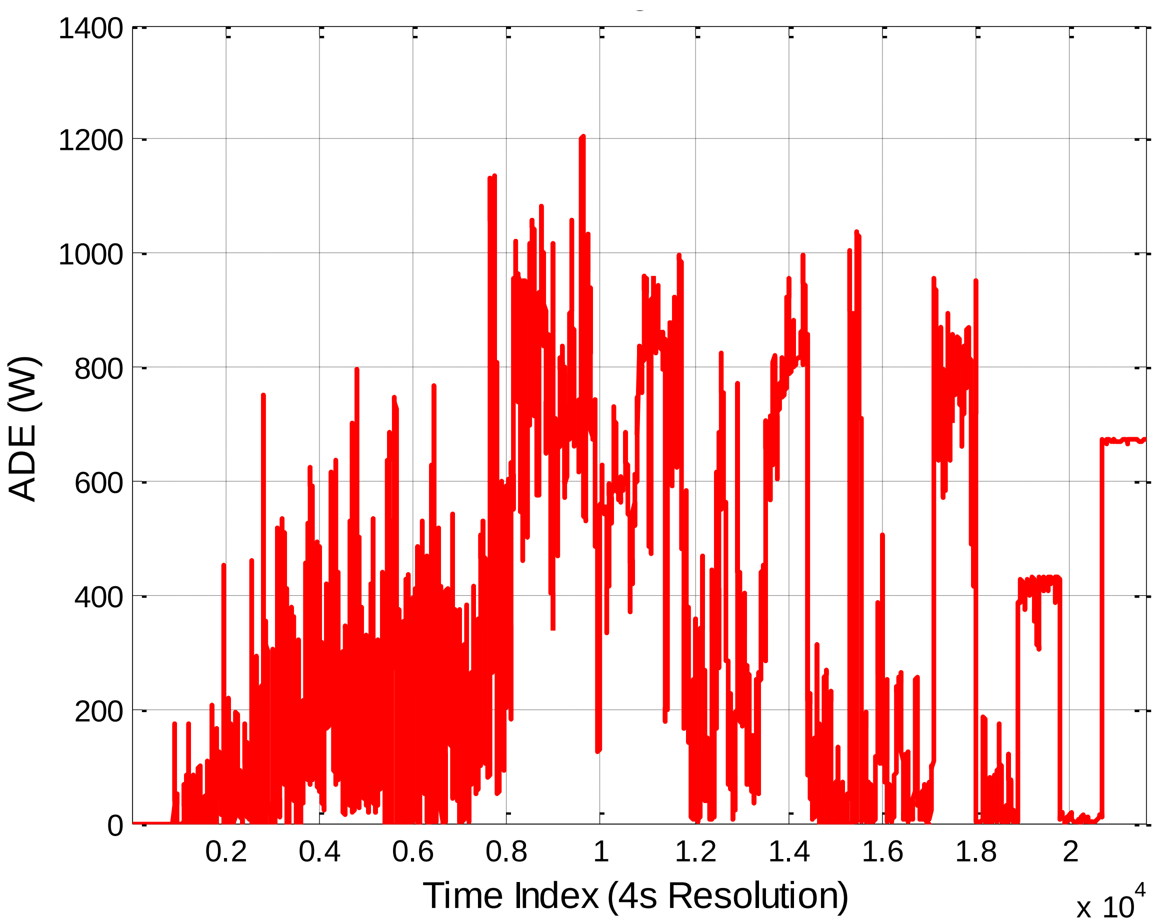

Figure 5. 4 Average ADE of Intelligent Dispatch Algorithm

Similarly, the *EDE* can be obtained as shown in figure 5.5 for all EVs during each time instance of the analysis.

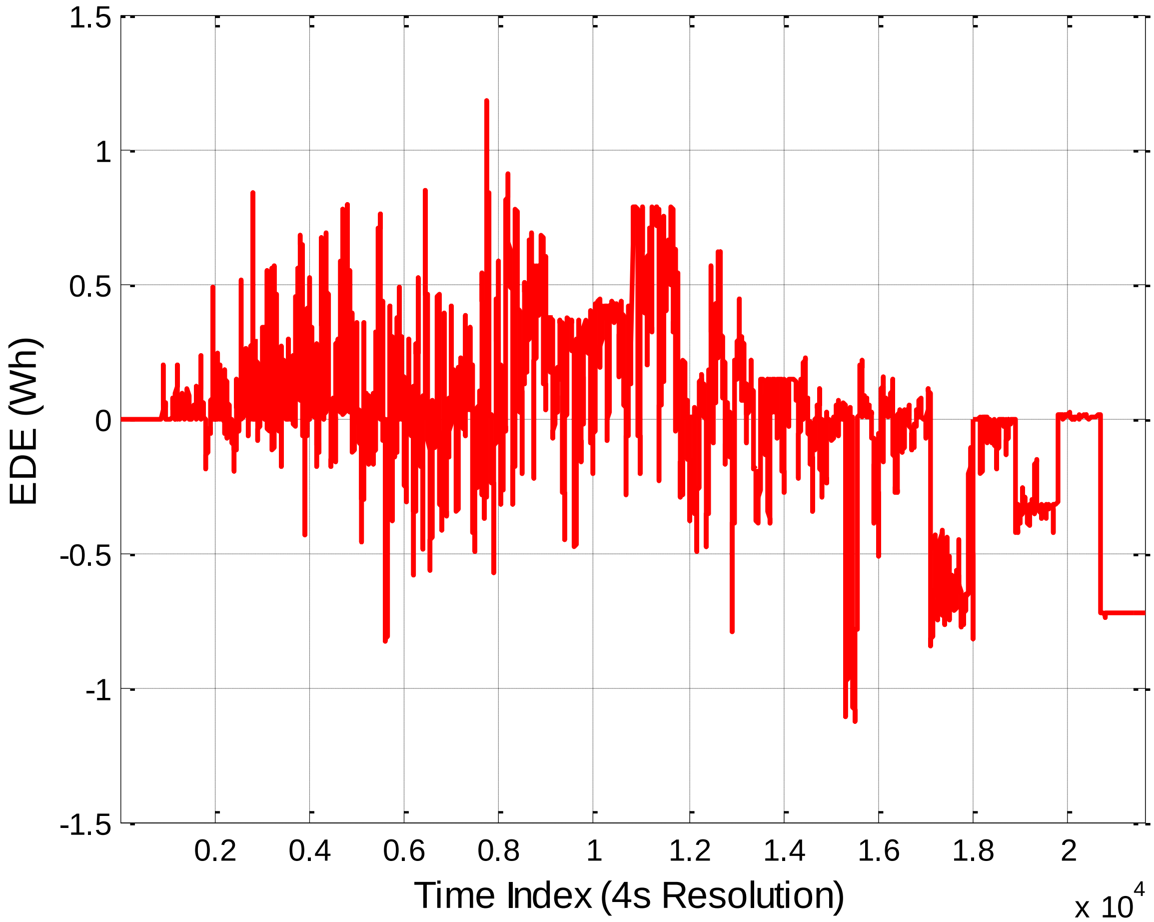

Figure 5. 5 Average EDE of Intelligent Dispatch Algorithm

5.3 Optimal Dispatch Algorithm (Discrete Mode)

In this section, the 1st formulation of the optimal dispatch algorithm will be applied to the same schedule from before and the obtained results will be compared with the conventional intelligent dispatch algorithm [24].

It is worth mentioning that the optimal dispatch algorithms were efficiently coded for optimized speeds such that each optimization per time instant takes around 0.25s to find a solution. This is considered fast enough since the developed schedule had 4s resolution. Thus leaving enough time for handling communication trafficking and sending and receiving signals.

The chosen values of the weighting constants S and F were 1 and $1/10000^2$ respectively. The reason $F \ll S$ is due to the nature of the units and maximum values of total switching and total *FDE*. The highest number of switching instances is equal to the total number of EVs in the system, which is 1000 in this case. On the other hand, *FDE* can sometimes represent a percentage difference and other times the absolute difference and therefore can have magnitudes in orders of thousands of kWs.

The dispatch operating point of the optimal dispatch followed the schedule throughout the entire analysis duration exactly as in figure 5.2. This is due to the availability of enough EVs to meet the schedule as shown in figure 5.6.

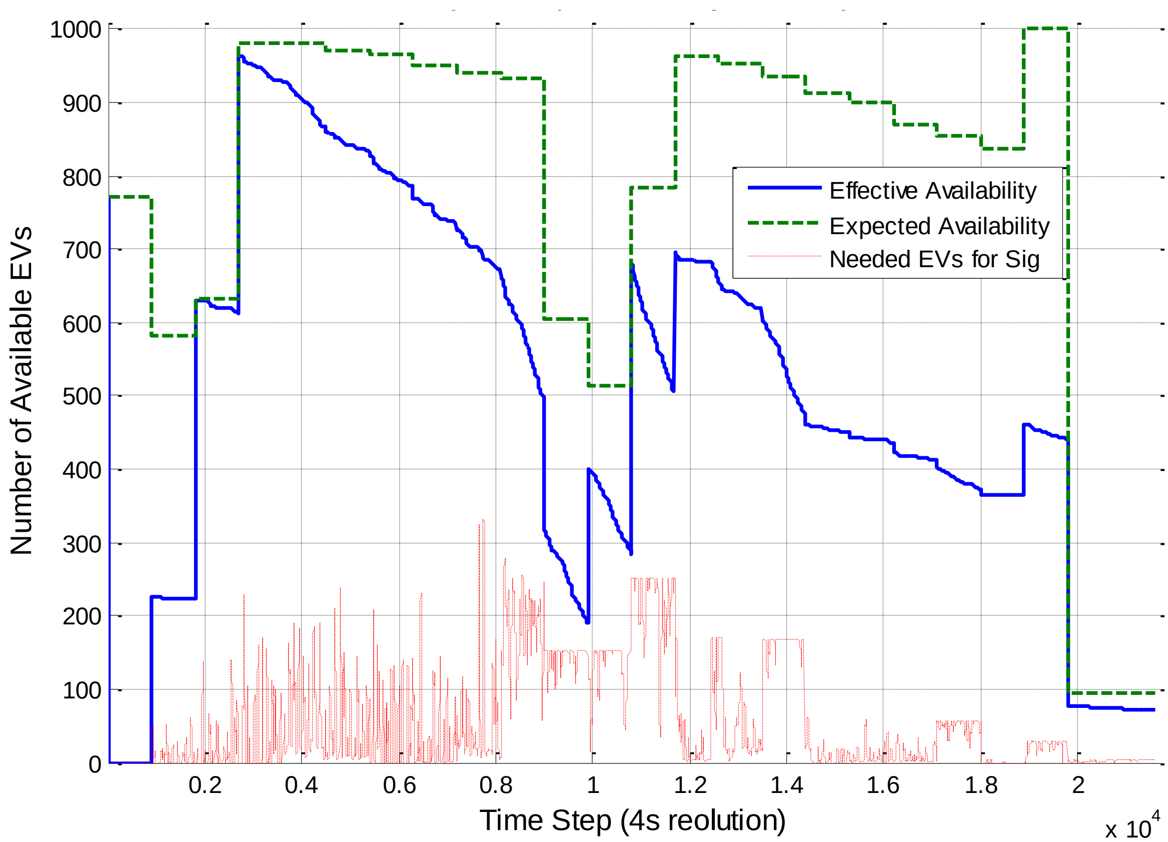

Figure 5. 6 EV Availability for Optimal Dispatch throughout Analysis Period

The overall results are summarized below in table 3. It can be seen that the optimal dispatch model performs better than the conventional one in all aspects overall.

Table 3 Performance Evaluation of Optimal Dispatch Algorithm (1st Formulation)

Total # of Messages	Overall Mean ADE (W)	Overall Mean EDE (Wh)	EV Violations
32979	330.4183	-0.004166	38

Since the overall results were not significantly better than the intelligent dispatch model. We still need to extend the analysis and compare the models in more details.

If we consider the final SOC of all EVs and normalize them over their respective targets if incremental dispatch is used, we get the charge percentage left in each EV by the end of analysis which can be higher or lower than the target. The normalized final SOC profile is shown in figure 5.7 below. It can be seen that the optimal dispatch algorithm is performing better overall and the EVs are meeting their targets faster and getting in general more energy as compared to the conventional model. This can be expected by inspection of the overall mean EDE which is higher for the optimal model. As for the first few EVs in figure 5.7, it might seem that the optimal dispatch algorithm is performing worse and a few EVs aren't receiving enough energy. This is not necessarily the case since fairness with respect to incremental dispatch must also be considered. The optimal model performs better because it takes the actual incremental dispatch signal as reference for fairness (4.1.16)-(4.1.18) whereas the conventional intelligent model uses expected values of energy (3.1).

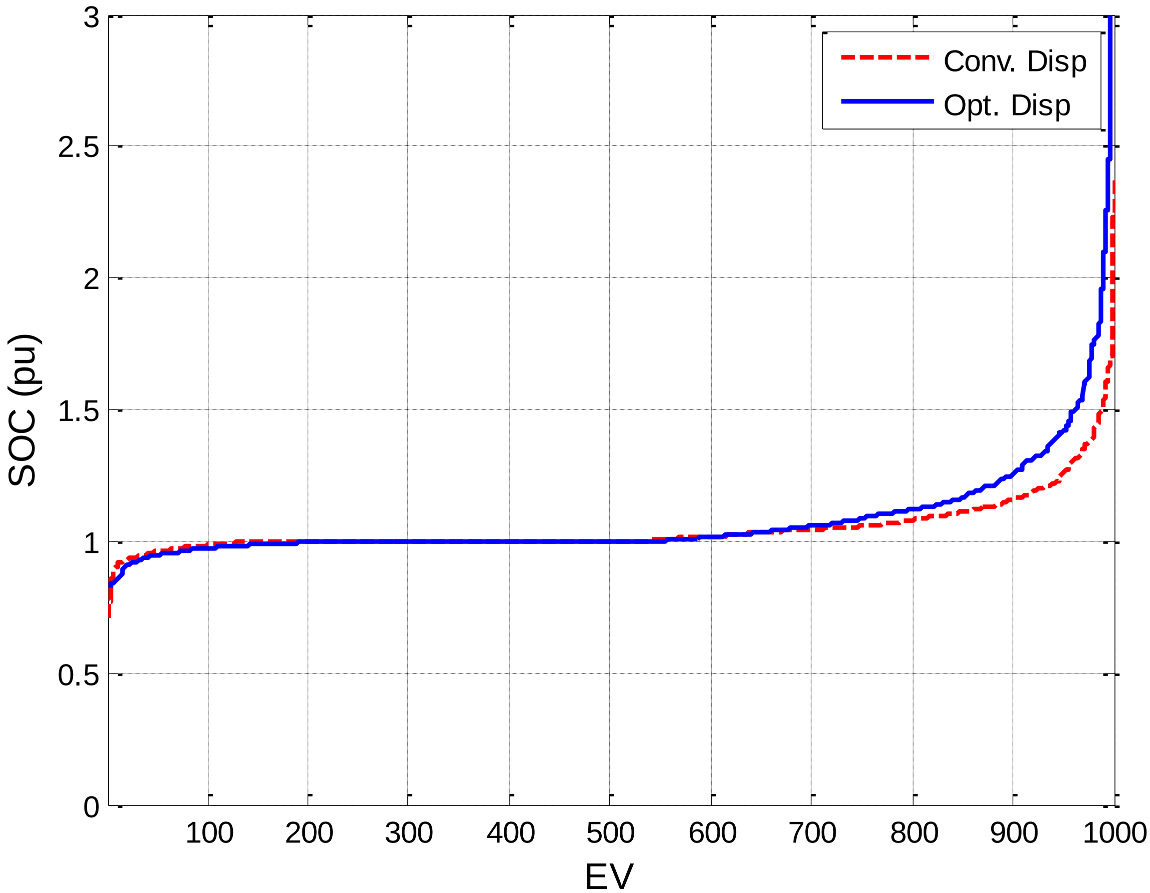

Figure 5. 7 Normalized Final SOC Profile Coparison Between the Conventional and Novel Models

The mean *ADE* of the optimal dispatch was lower than the intelligent dispatch. This can be seen in more details from figures 5.8 and 5.9 which respectively show a comparison between the average *ADE*s of the two models and the equivalent hourly representation.

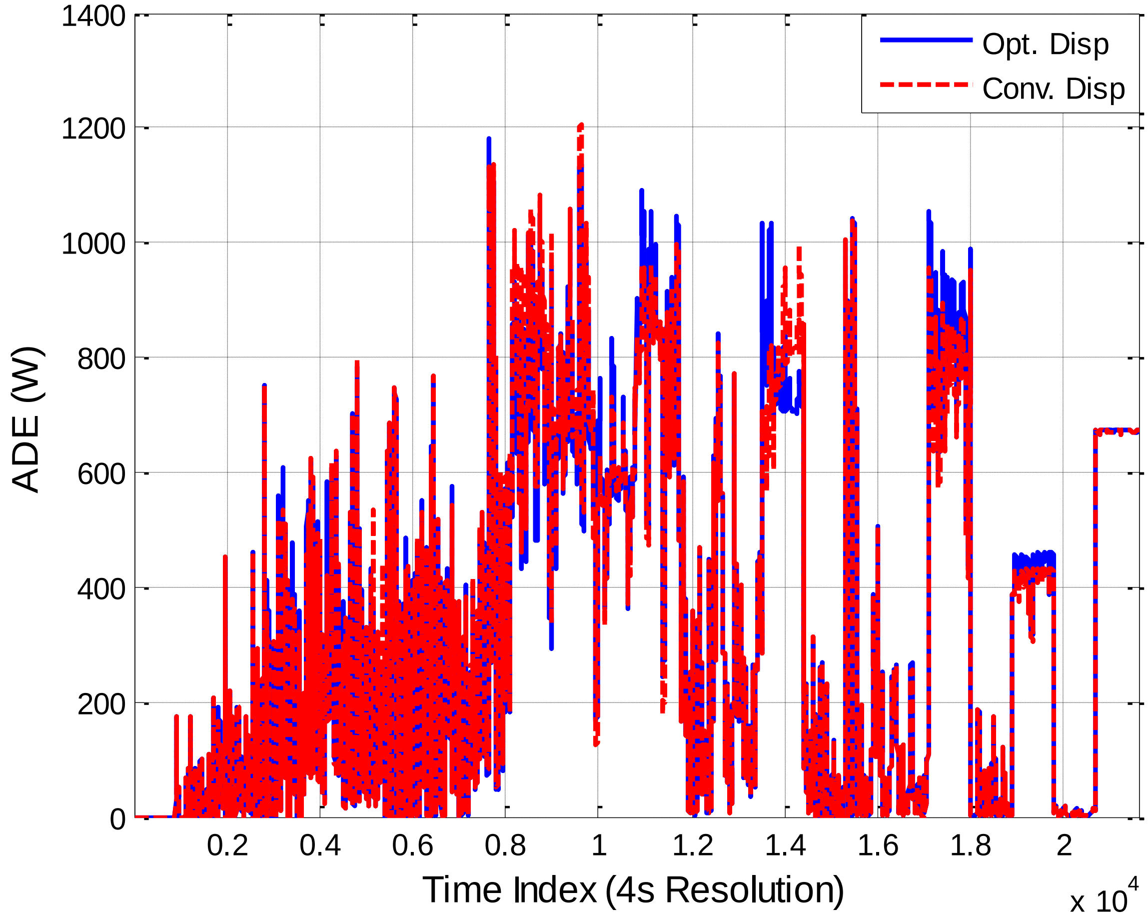

Figure 5. 8 Average ADE Comparison of the Optimal and Intelligent Models

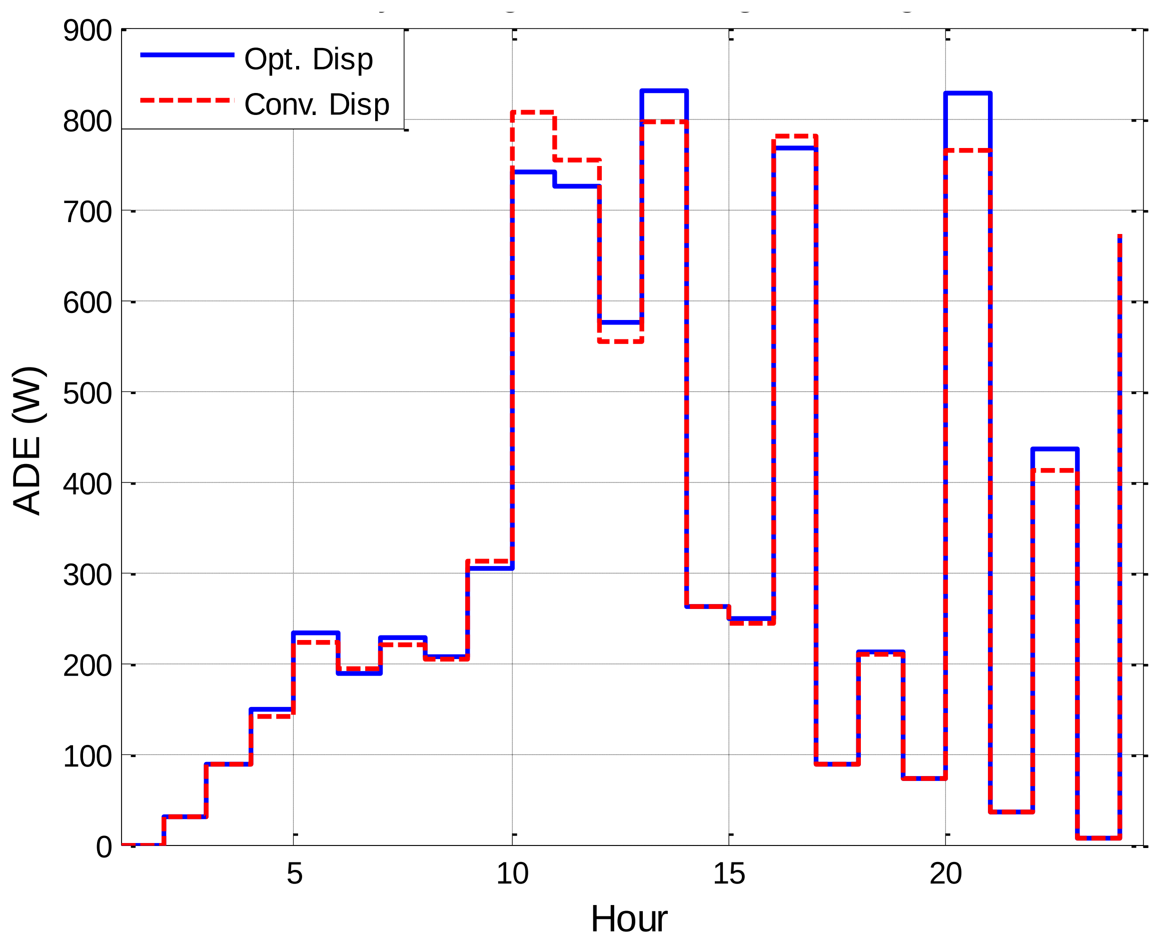

Figure 5. 9 Hourly Average ADE Comparison of the Optimal and Intelligent Models

Even though the differences between the overall mean ADEs of the two algorithms were not large, figure 5.10 below shows the EVs' mean ADE. It can be noticed that Even though overall mean ADE is almost the same for both models, it can be seen that for the worst cases the differences are relatively larger than the others (optimal model 200-300W better).

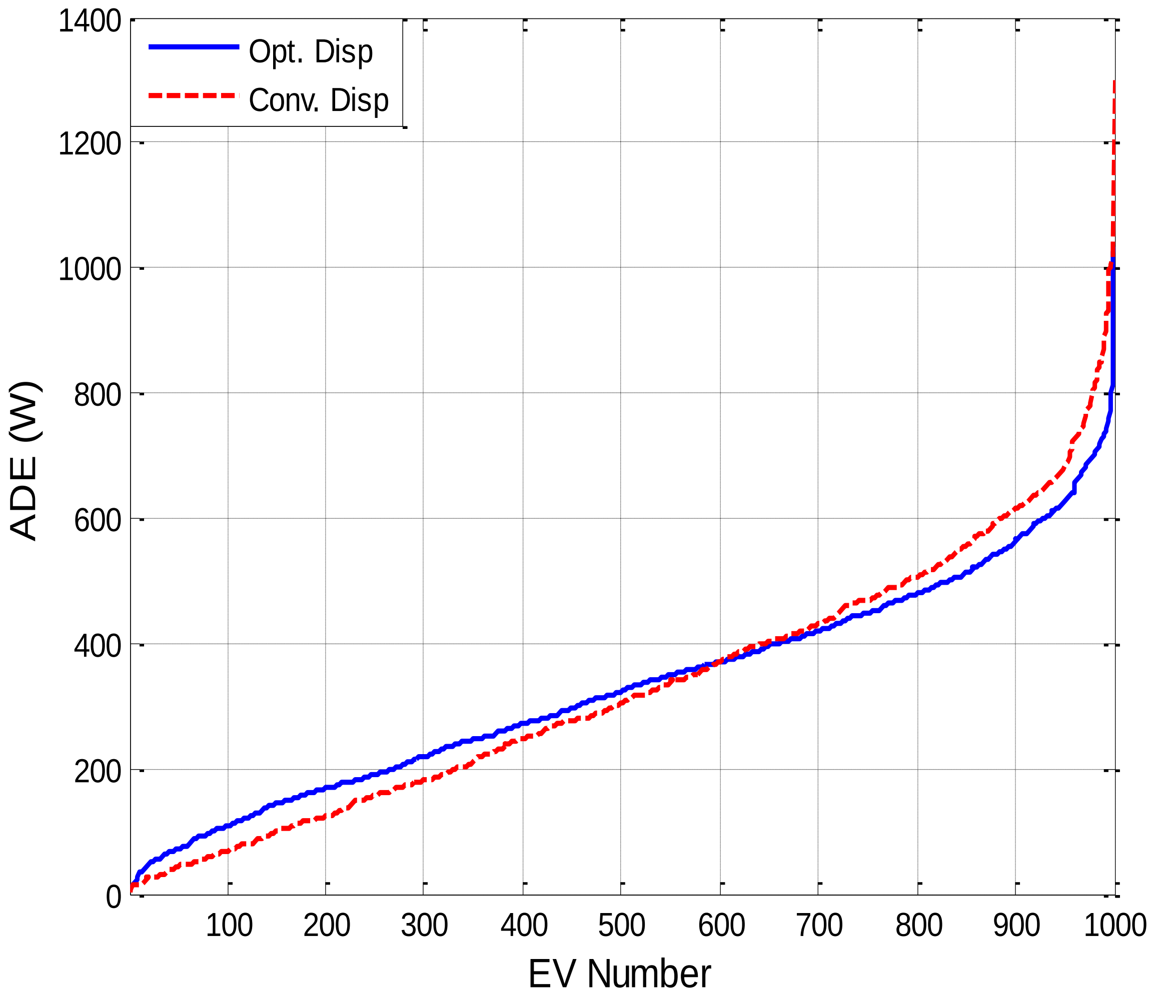

Figure 5. 10 Sorted Average ADE per EV

The accumulated mean *EDE* of the optimal dispatch was higher than the conventional dispatch. This can be seen in more details from figure 5.11 which shows a comparison between the mean accumulated *EDE*s of the two models. It can be noticed that since both models follow the same schedule, the get the same energy and hence on average would have almost identical mean accumulated energy errors.

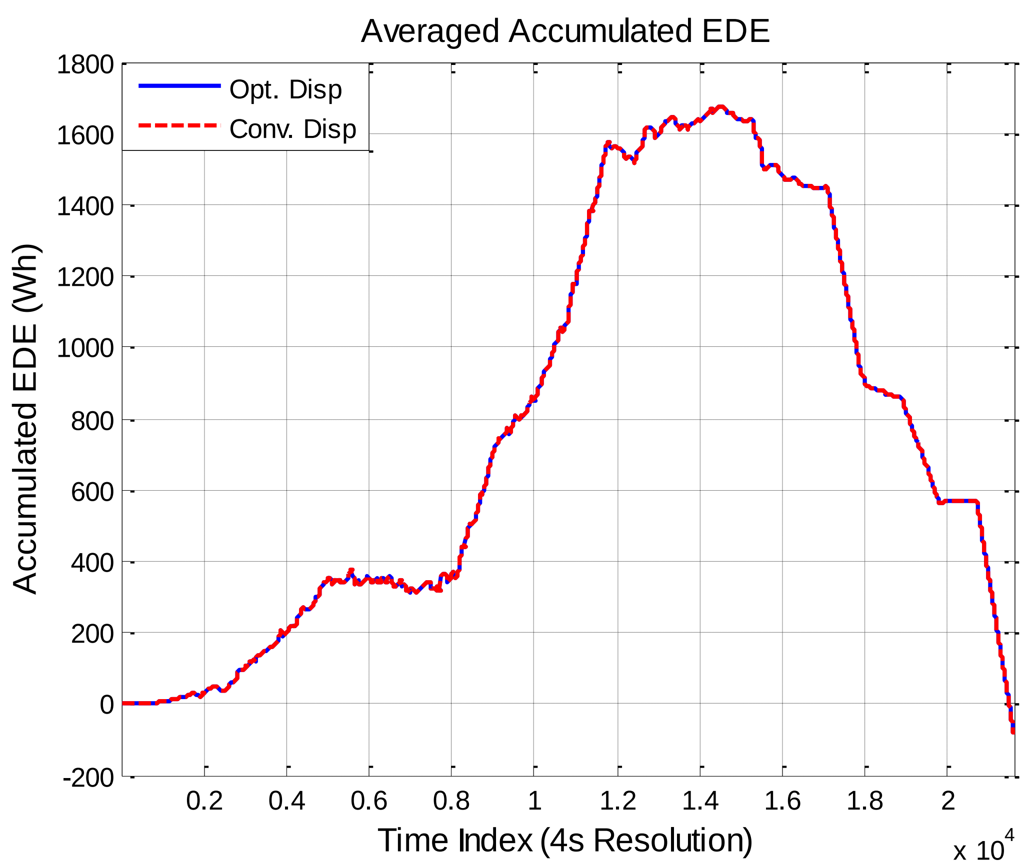

Figure 5. 11 Average Accumulated EDE Comparison of the Optimal and Intelligent Models

Figure 5.12 depicts the total accumulated *EDE* per EV sorted in ascending order. As expected, since both algorithms get the same energy, the general trend for all EVs have almost identical accumulated energy errors.

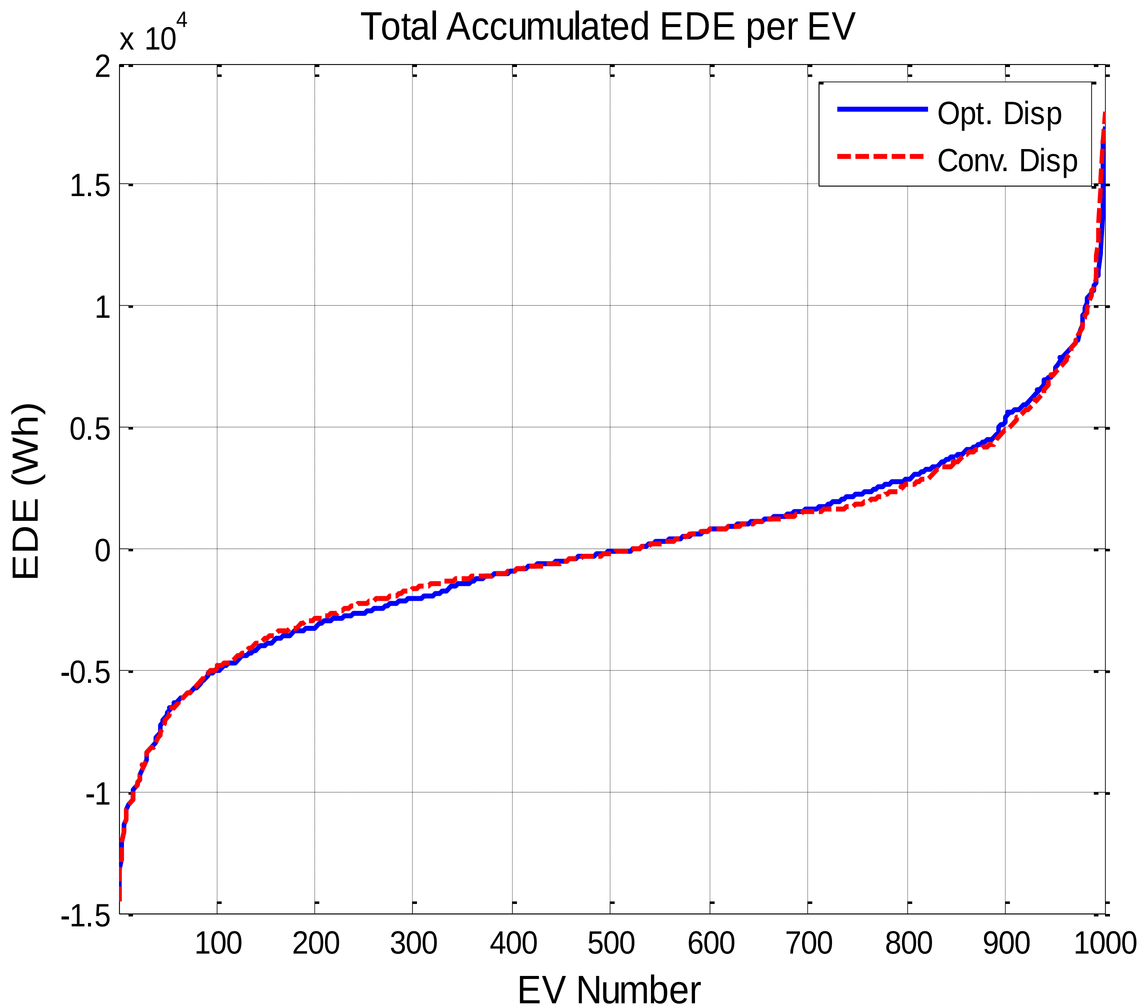

Figure 5. 12 Total Accumulated ADE Comparison of the Optimal and Intelligent Models

Moreover, it was found that the EV with lowest battery percentage left from both dispatch algorithms (lowest in figure 5.7) was EV#977. It can be seen from figures 5.13 and 5.14 that the optimal dispatch model followed the schedule better than the conventional model and consequently $SOC_{977,T}$ was higher since it followed the schedule with less accumulated energy errors.

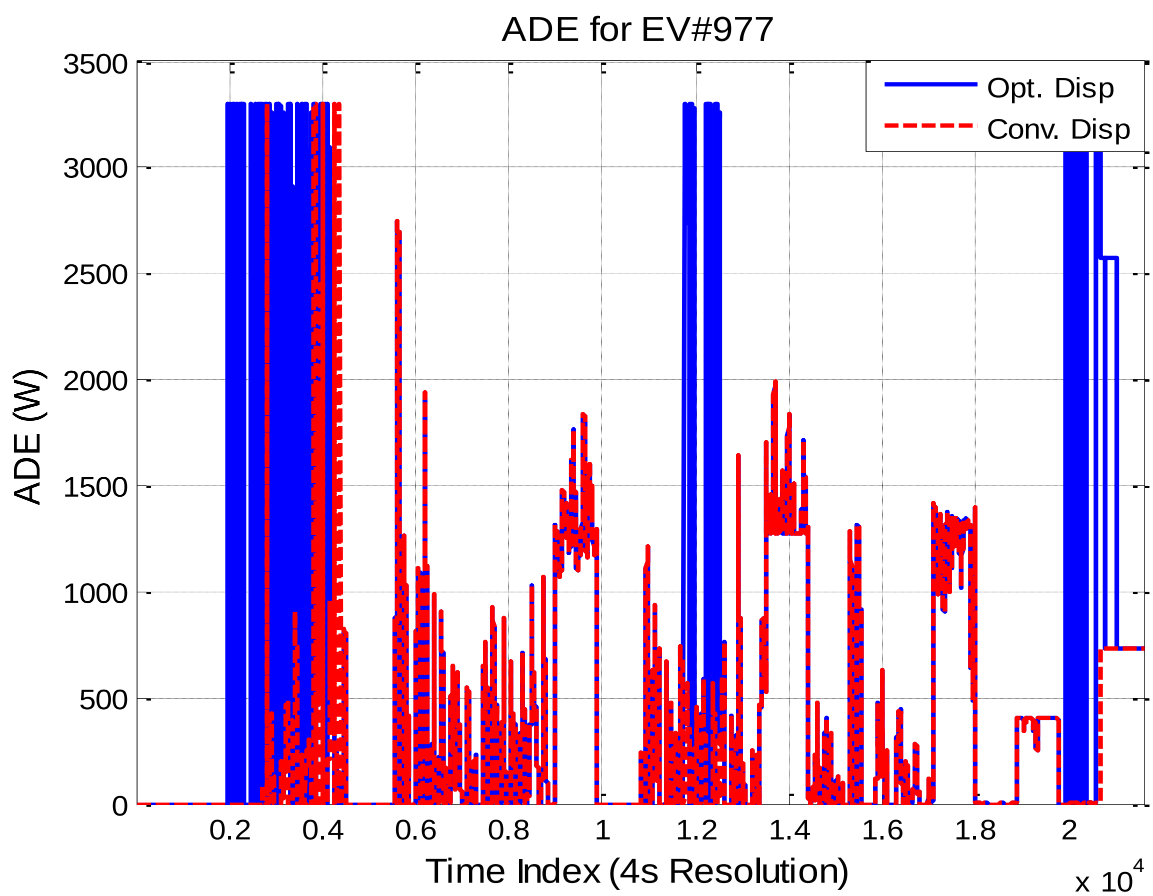

Figure 5. 13 Average ADE of EV 977 Comparison of the Optimal and Intelligent Models

Figure 5.14 below shows why EV 977 received lower SOC than target using the conventional model. It's shown that the optimal model tended to charge that EV closer to incremental dispatch most of the time as compared to the conventional model which had high negative errors (accumulated *EDE*) towards the end and thus farther from the schedule.

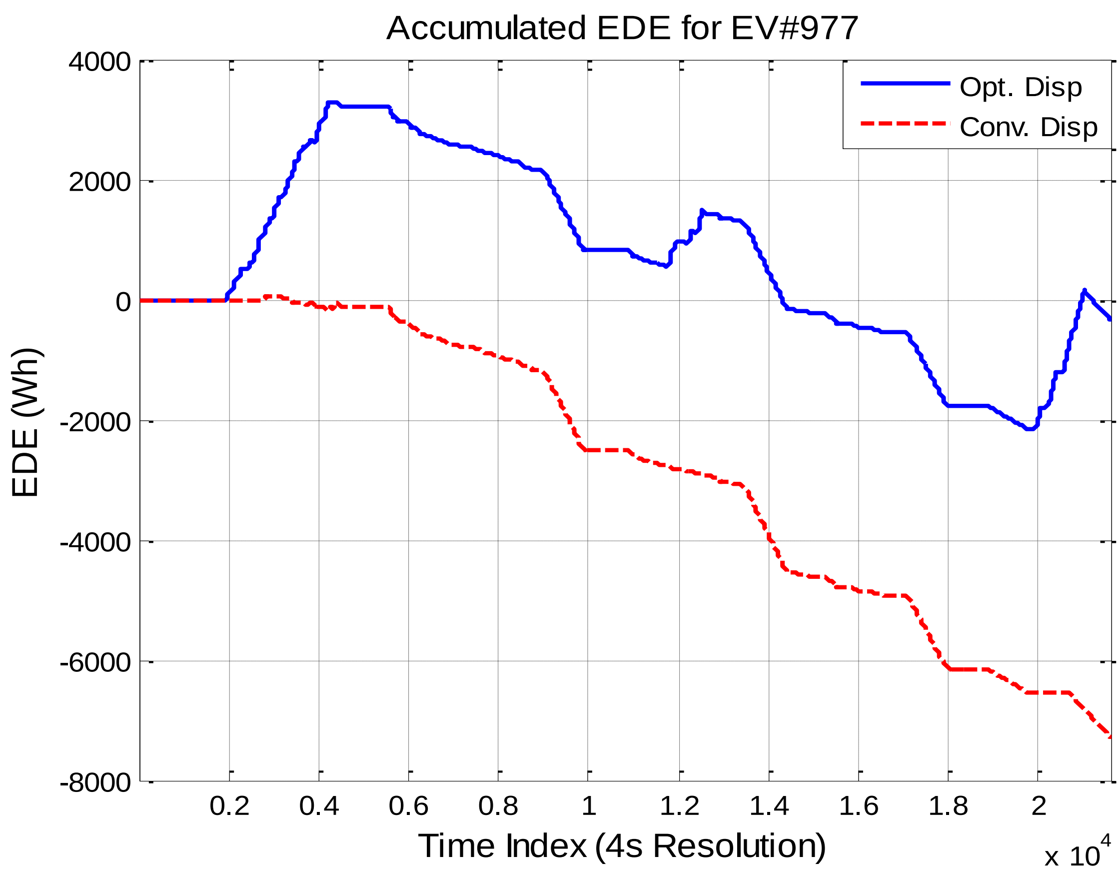

Figure 5. 14 Accumulated EDE of EV 386 Comparison of the Optimal and Intelligent Models

There is a huge difference between equally charging the EVs and in doing so fairly. It was mentioned before that the optimal algorithm used actual incremental dispatch signals as reference for fairness whereas the conventional algorithm depended on the expected values of energy to be received making the developed model more reliable in fairly dispatching EVs.

It was seen before that there are more violations using the conventional algorithm since its overall behavior trends to equally dispatch the EVs while just prioritizing EVs with higher expected energy to be received. Since the optimal algorithm uses actual values of energy as reference, not only were the violations less but they were on the cars with the least scheduled energies. Moreover, the EVs were fully charged faster using the optimal dispatch algorithm according to their schedules. The explained behaviors of the two models can be also perceived from figures 5.3 and 5.6. It can be noticed that the effective availability of the EVs performing optimal dispatch decreases much faster and steeper than when dispatched using the conventional model. Also the total number of EVs effectively available by the end of the analysis period was significantly lower in optimal dispatch since they became fully charged.

5.4 Sensitivity Analysis

5.4.1 Sensitivity to Schedule

The previous sections contained results based on a schedule that has been set for a whole lump of 24 hours. It was performed such that no violations in following the given schedule would occur. However, what's more likely to happen in real time scenarios is that aggregators would keep updating and modifying their schedules based on the circumstantial events that occur and try to fully charge the available EVs. For instance, the aggregator would update the schedule each hour based on the total number of EVs currently available and expected to stay and for how long. It would therefore be interesting to observe how the system would behave if more energy was scheduled by the aggregator.

In this part of the analysis, the overall base schedule was multiplied by a factor of 3. This value was chosen such that the scaled maximum value of the schedule would be just below the dispatch capability of the system assuming all the 1000 EVs are available. The tests were performed using both the conventional and optimal dispatch algorithms. The optimal dispatch algorithm had the same parameters as in the base case (S=1; F=1/15000^2).

Now since there is more total energy, this would inherently overburden the aggregator's EV system since the overall energy that the EVs would require to fully charge would be lower than the total energy requirements form the SO. It was seen that the majority of the EVs were fully charged in the base case using any of the two algorithms. Figure 5.15 depicts the actual dispatch operating point and how it tries to follow the supplied schedule and figure 5.16 shows it as a percentage of the schedule. These figures would help the aggregator determine approximately how much lower than the base case to schedule their dispatches.

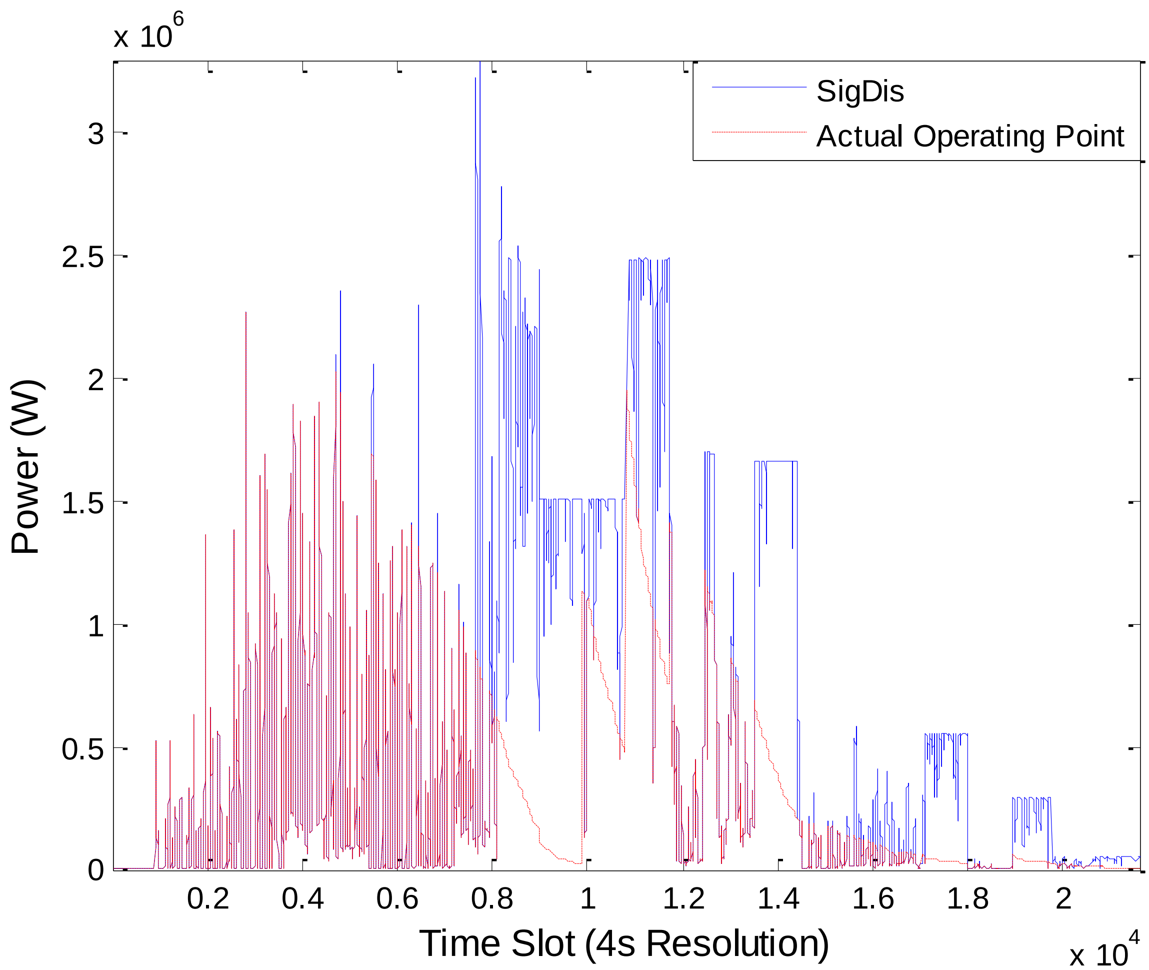

Figure 5. 15 Intelligent Dispatch Operating Point Following Scaled Scheduled Deployment Signal

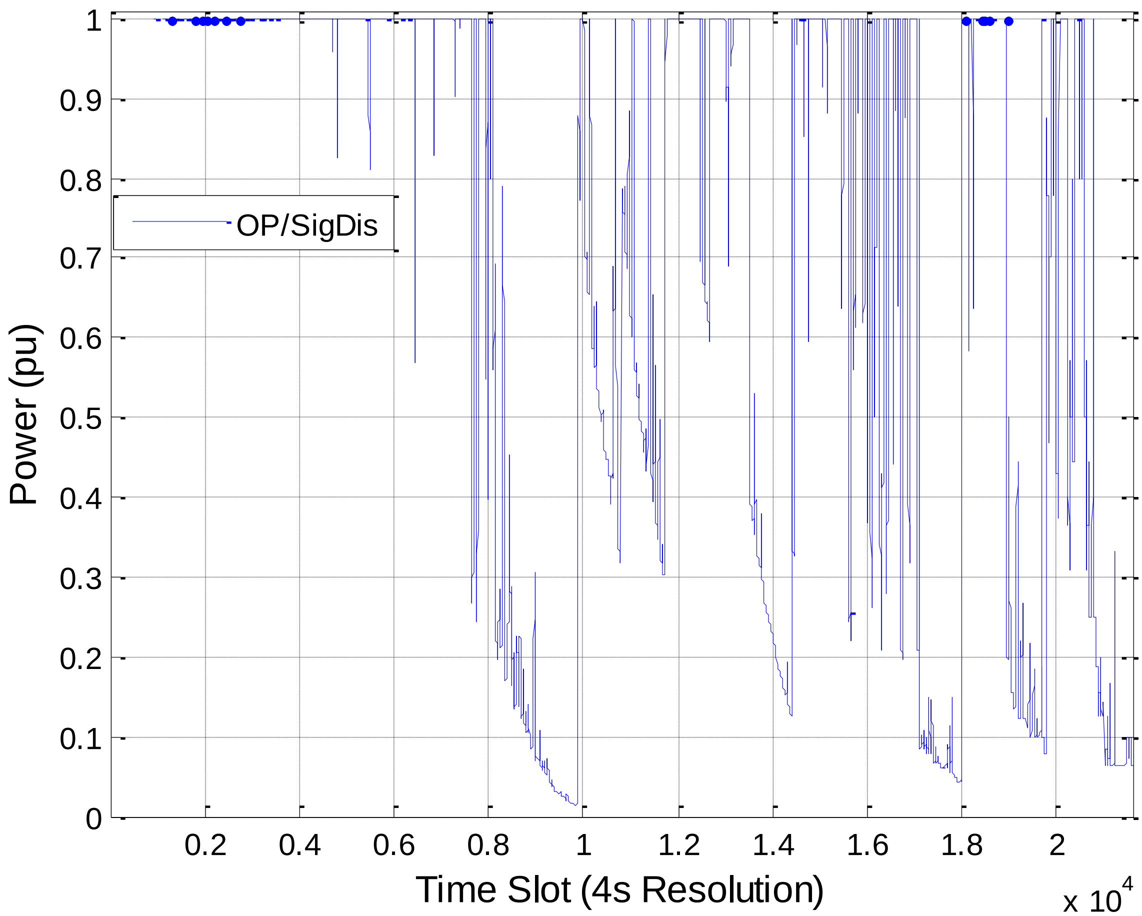

Figure 5. 16 Intelligent Dispatch Operating Point as a Percentage of Scaled Deployment Signal

The overall performance evaluation results are displayed in table 4 below. It can be seen that when the aggregator updates the schedule such that all EVs are charged, the differences between the two dispatch models become more significant. The optimal dispatch model completed the simulation with a bandwidth reduction of 20.69% less than the conventional model. In addition, the overall mean *ADE* between the actual and incremental dispatch was 53.64% lower when the novel optimal model was implemented. The conventional model in general was inclined to give less energy to the EVs than from incremental dispatch opposing to the optimal model which gave more energy than incremental dispatch.

Table 4 Performance Evaluation Comparison Between the Novel and Conventional Models Applied on Scaled Schedule

Model Type	Total # of Messages	Overall Mean ADE (W)	Overall Mean EDE (Wh)
Optimal	51085	673.1517	-0.26583
Conventional	66019	704.9929	-0.25542

The numbers in this case are higher than the bench mark case can be due to several factors. One aspect is that fully charging EVs makes them effectively unavailable for dispatch as explained before. Having more total energy to fully charge more EVs will consequently lead to requiring extra messages to be sent for cars that are still available to switch states. Now with too much energy to consume, the effects of receiving a deployment signal much higher than the base case regulation signal can be observed clearly. Cars that get fully charged not only lead to increasing communication requirements but would also lead to instances where the signal itself couldn’t be met. The reason is because not enough cars would be available for dispatch if they’re effectively unavailable.

Figures 5.17 and 5.18 show the explained effects and its propagation through the analysis period. Initially, the number of EVs required to meet the signal was lower than the available EVs for dispatch and thus no schedule violation were experienced. As more and more EVs get charged, less cars will be available to meet the required signal until all cars are fully charged.

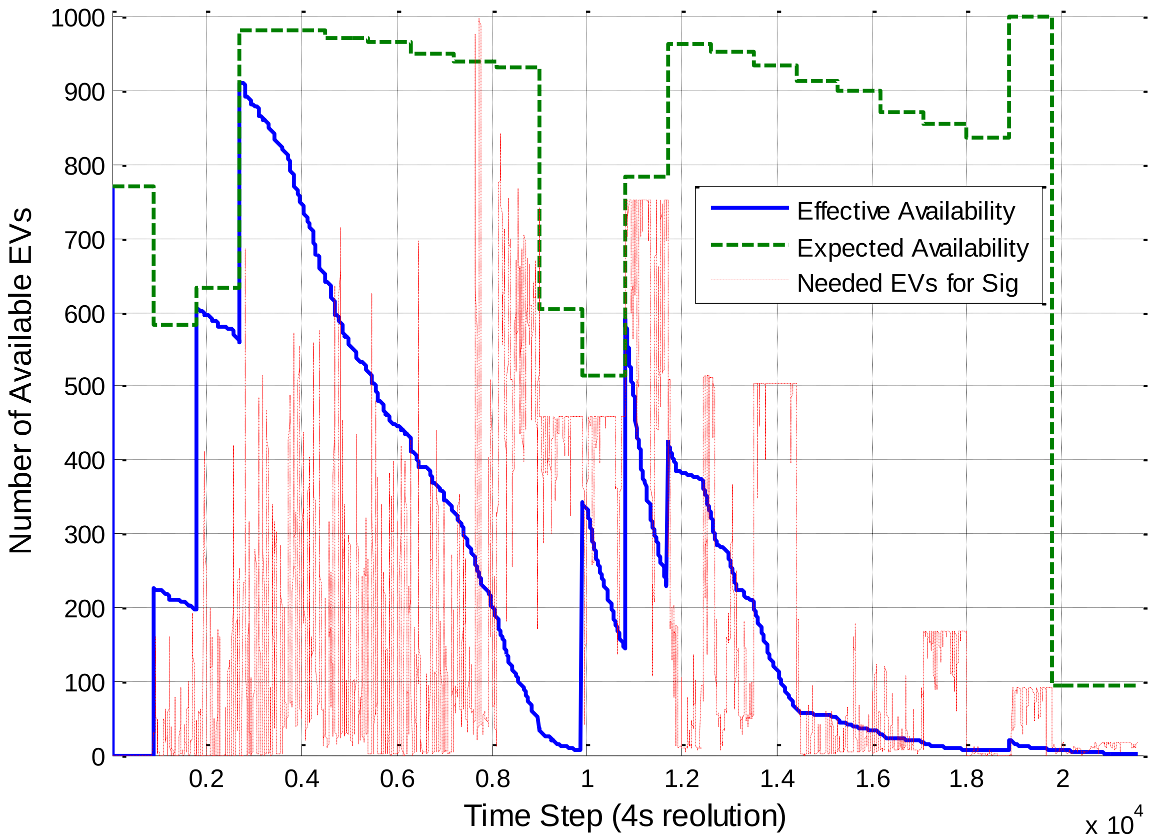

Figure 5. 17 EV Availability for Intelligent Dispatch Throughout Analysis Period of Scaled Schedule

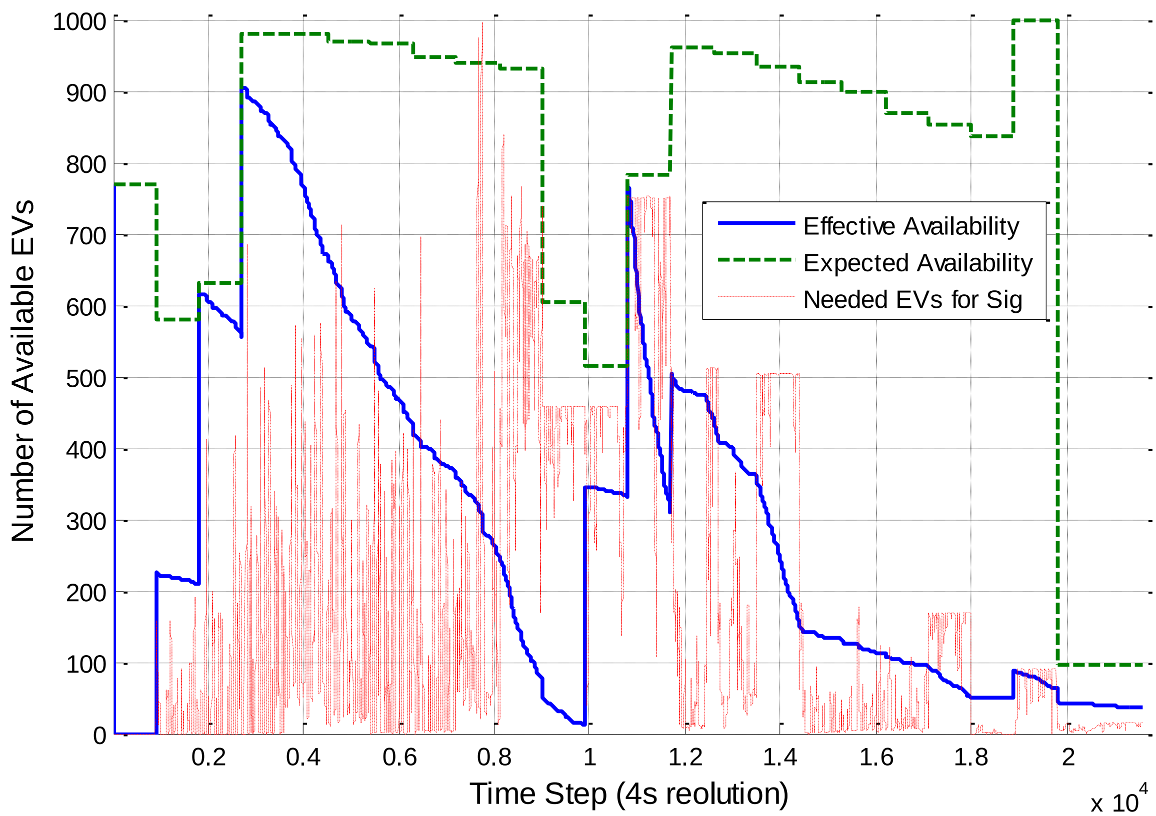

Figure 5. 18 EV Availability for Optimal Dispatch Throughout Analysis Period of Scaled Schedule

We also want to consider the detailed performance results. Figures 5.19 shows the hourly averaged *ADE* through time. It's noticeably lower for the optimal model the majority of the time.

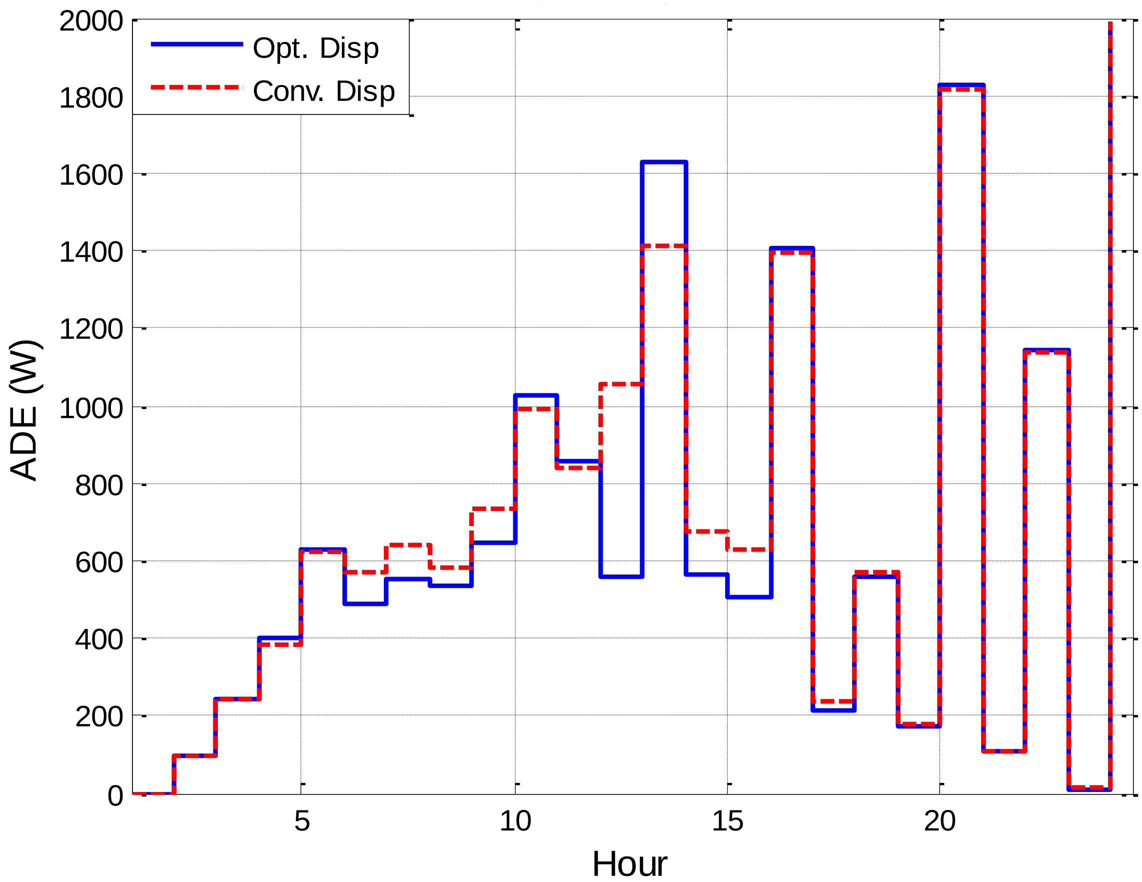

Figure 5.19 Hourly Mean ADE Comparison Using the Scaled Schedule

Figure 5.20 below shows the mean accumulated *EDE* through time. It can be seen that the optimal model's final value is almost equal to the conventional model.

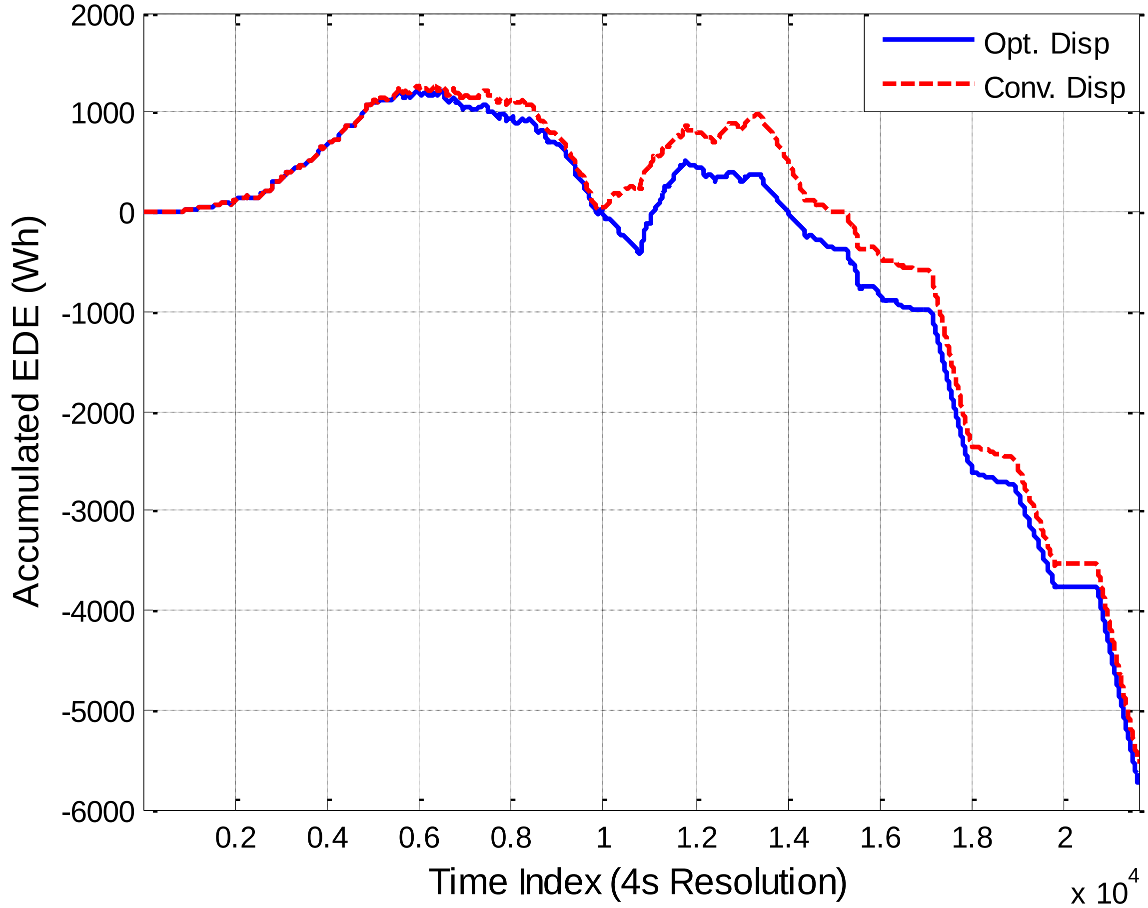

Figure 5.20 Mean Accumulated EDE Comparison Using the Scaled Schedule

Figure 5.21 shows the mean *ADE* of each EV after the analysis was conducted. It can be seen that the optimal dispatch model was efficient in maintaining fairness for more than half of the EVs in addition to being conservative in terms of communication traffic requirements. The EV with highest *ADE* in the optimal model was lower than its correspondent in the conventional model.

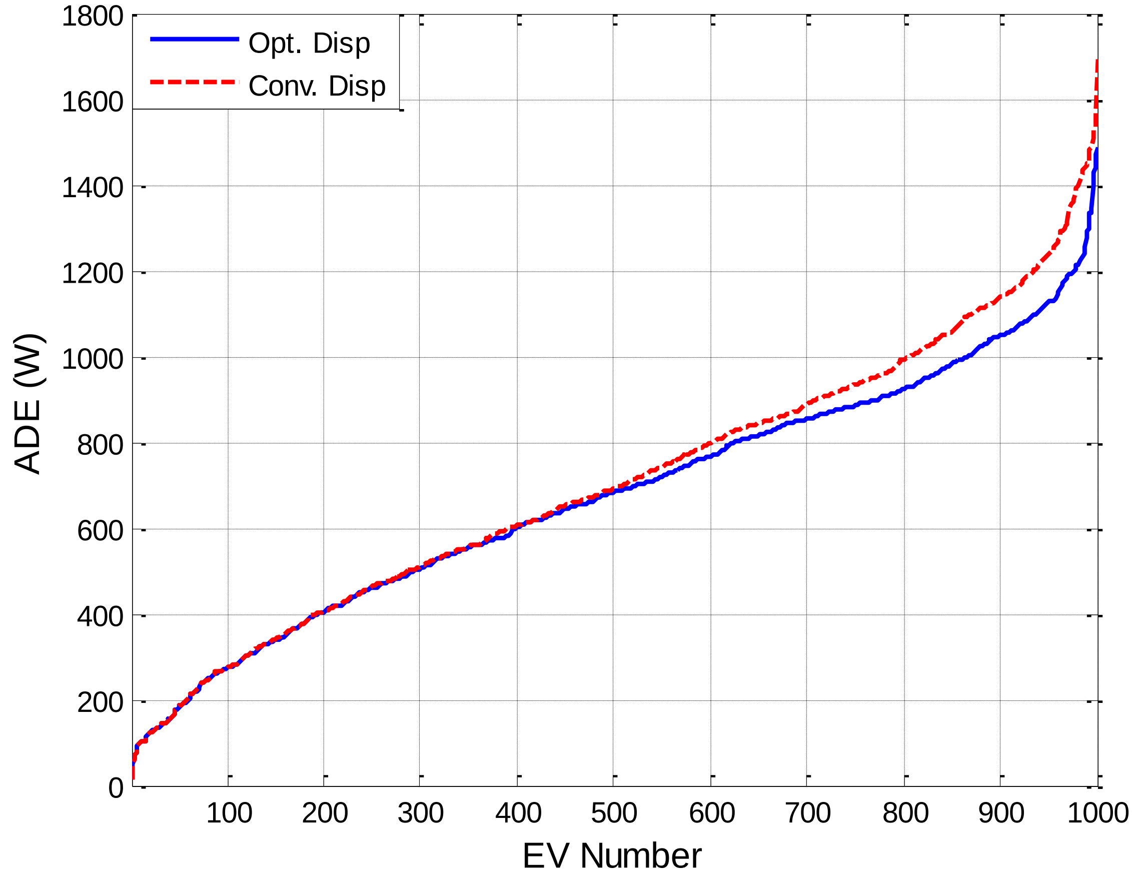

Figure 5. 21 Mean ADE per EV Comparison Using the Scaled Schedule

Figure 5.22 shows the total accumulated *EDE* of each EV after the analysis was conducted. It can be seen that the optimal dispatch model was more efficient in maintaining fairness for all EVs in addition to being conservative in terms of communication traffic requirements. The highest accumulated *EDE* in the optimal model was lower than the highest of the conventional model. It can be observed that on average the optimal model is closer to the zero axis and has a flatter profile than the conventional model.

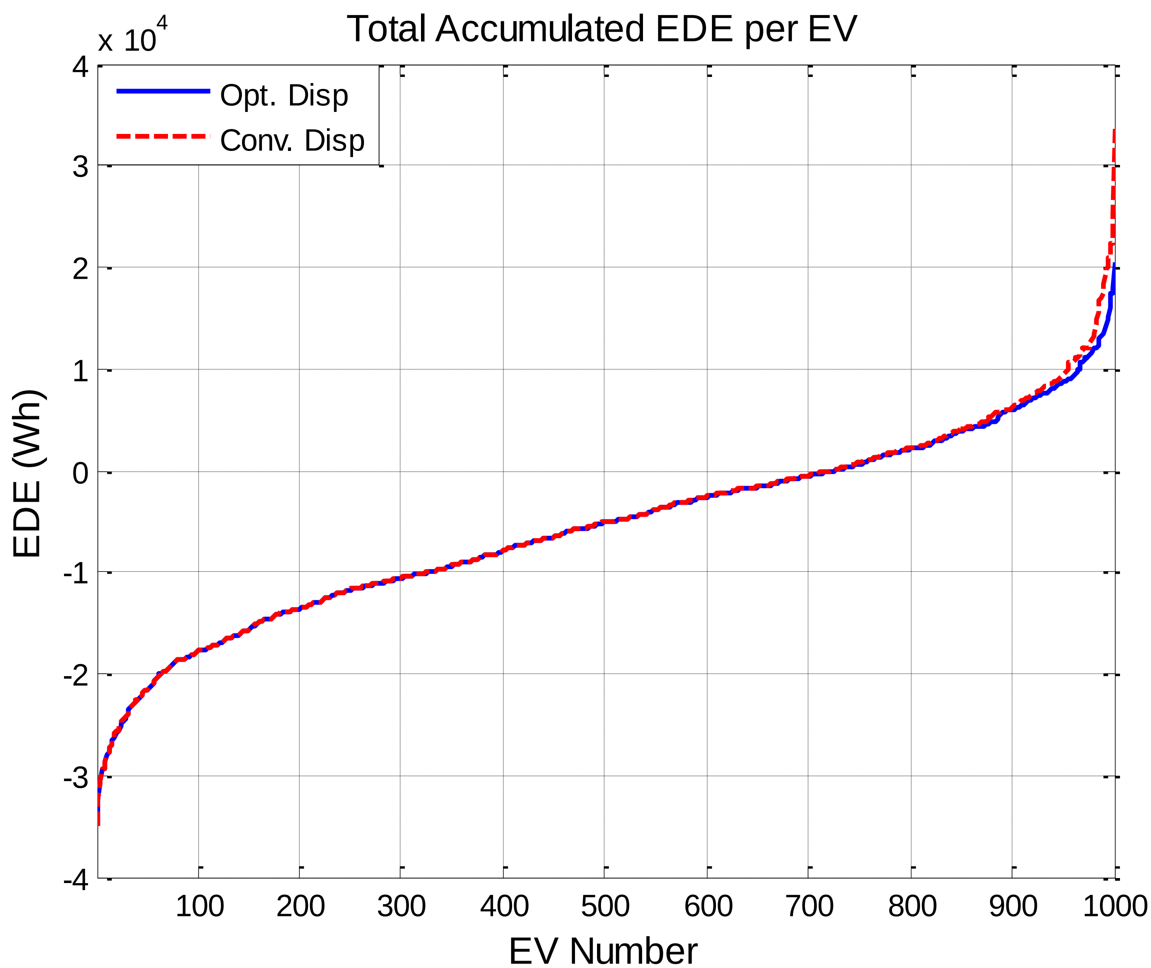

Figure 5. 22 Total Accumulated EDE per EV Comparison Using the Scaled Schedule

5.4.2 Sensitivity to Weighting Constants

In this section, the effects of varying the weighting constants *S* and *F* will be investigated on the optimal dispatch mode from section 6.3. The value chosen for *S* was kept 1 while varying *F* to values above and below the base value of $1/10000^2$. The overall results are summarized in table 5 below. The EV violations as before represent the number of EVs with final SOC below their targets if incremental dispatch was used.

It can be noticed that when the weight of fairness increased, this increased the total communication BW requirements. This is mainly due to reducing the optimizer's flexibility in dispatch by putting more weight in following incremental dispatch. Moreover, the overall mean *ADE* is inversely proportional with the value of *F*. As expected, increasing fairness would decrease the absolute error in dispatch. However, the mean *EDE* was interestingly found to be directly proportional to *F*. As the value of *F* increased, the optimal model tended to give more energy to the EVs, on average, than incremental dispatch. The number of EV violations was found to increase with fairness. This is probably due to the optimizer minimizing switching more under lower values of *F*. If EVs keep on charging with less absolute error in dispatch, it's more likely they meet their targets faster than the case were fairness weighs less. Thus potentially reducing EV violations.

Table 5 Sensitivity Analysis on the Novel Optimal Models for Various Values of the Weighting Constants

Case	*F*=	Total # of Messages	Overall Mean ADE (W)	Overall Mean EDE (Wh)	EV Violations
Base *F*	$1/10000^2$	32942	221.4625	0.12167	54
Higher *F*	$1/5000^2$	43925	209.01	0.12958	41

The overall analysis of the data previously discussed can be seen in more detail in the following figures. Figures 5.23 and 5.24 show the hourly average *ADE* and mean accumulated *EDE* respectively. It can be seen that, in general, the *ADE* is inversely proportional to F while the accumulated *EDE* is directly proportional to it. Similar conclusions can be made on figures 5.25 and 5.26 where figure 5.25 shows the mean *ADE* of each EV after the sensitivity analysis was conducted and figure 5.26 depicts the total accumulated *EDE* per EV.

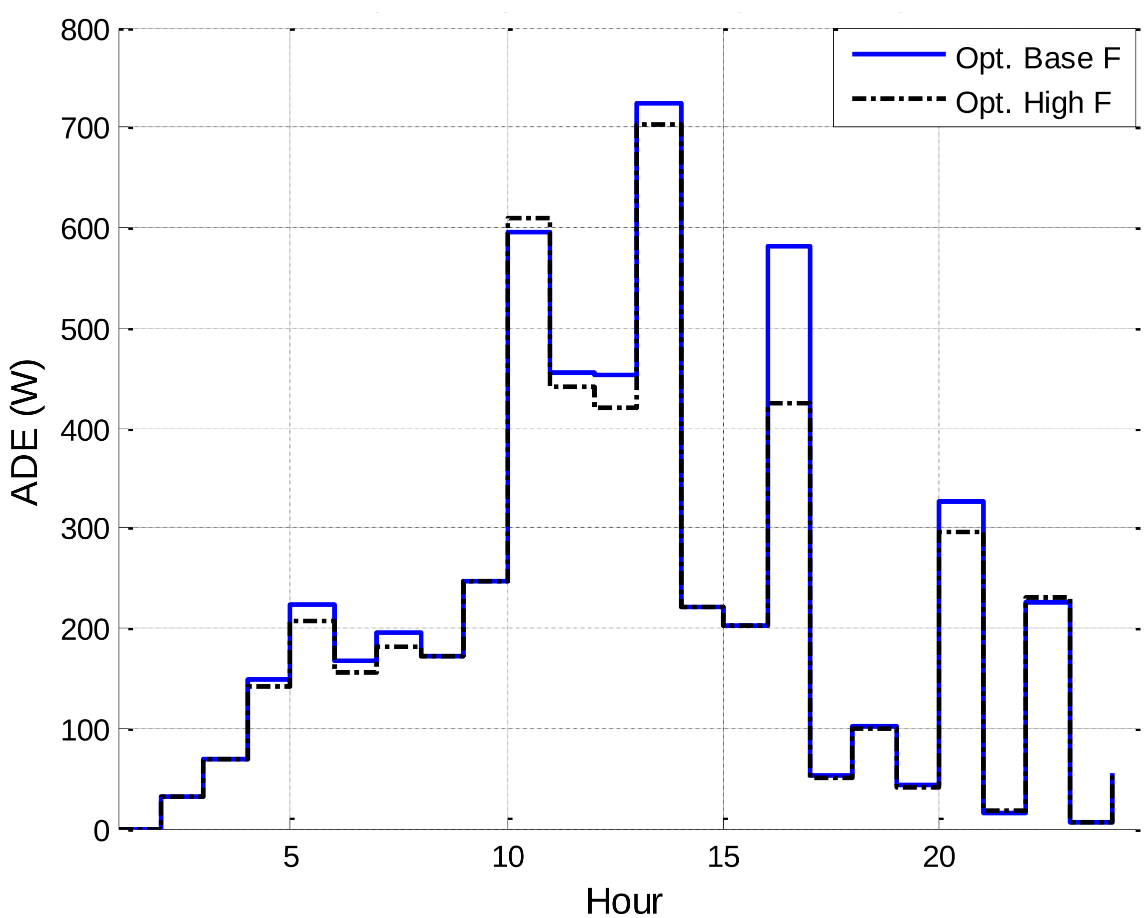

Figure 5. 23 Sensitivity Analysis on Hourly Averaged ADE using Optimal Model

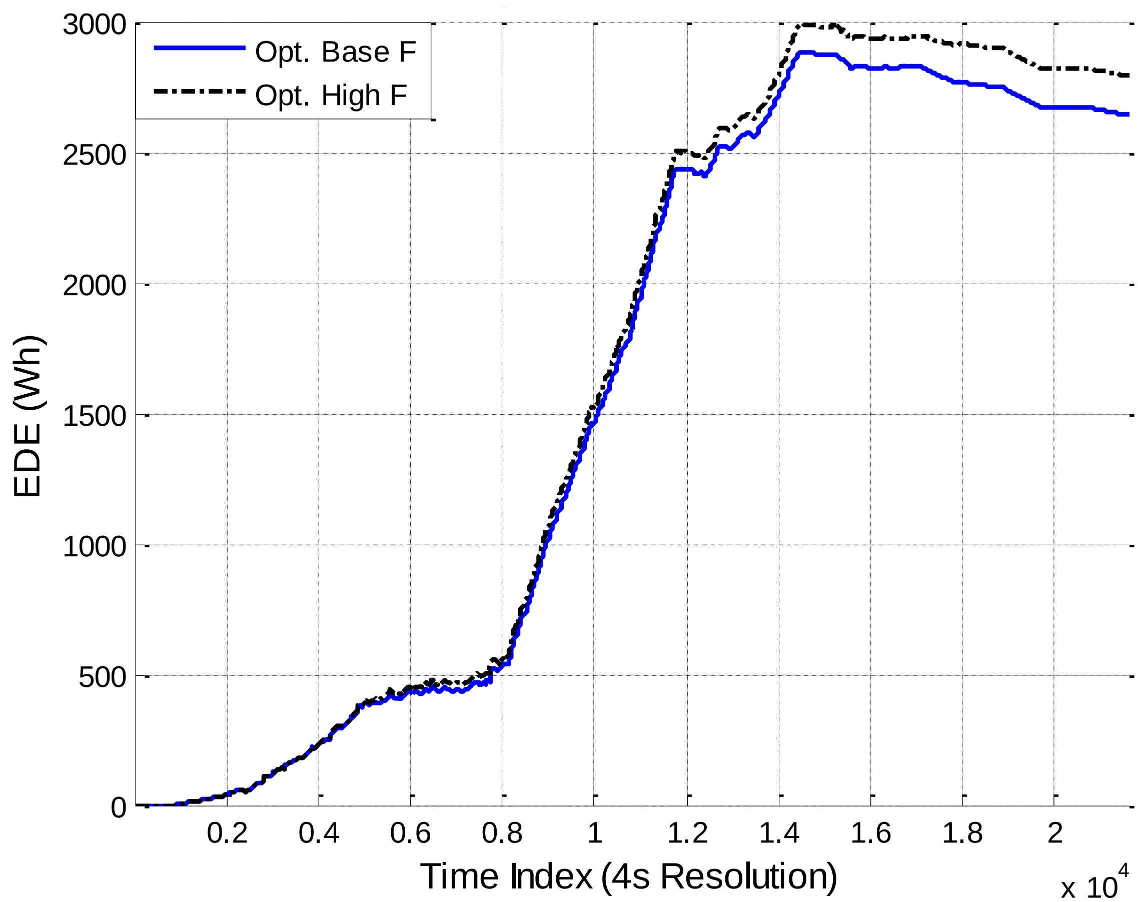

Figure 5. 24 Sensitivity Analysis on Averaged Accumulated EDE using Optimal Model

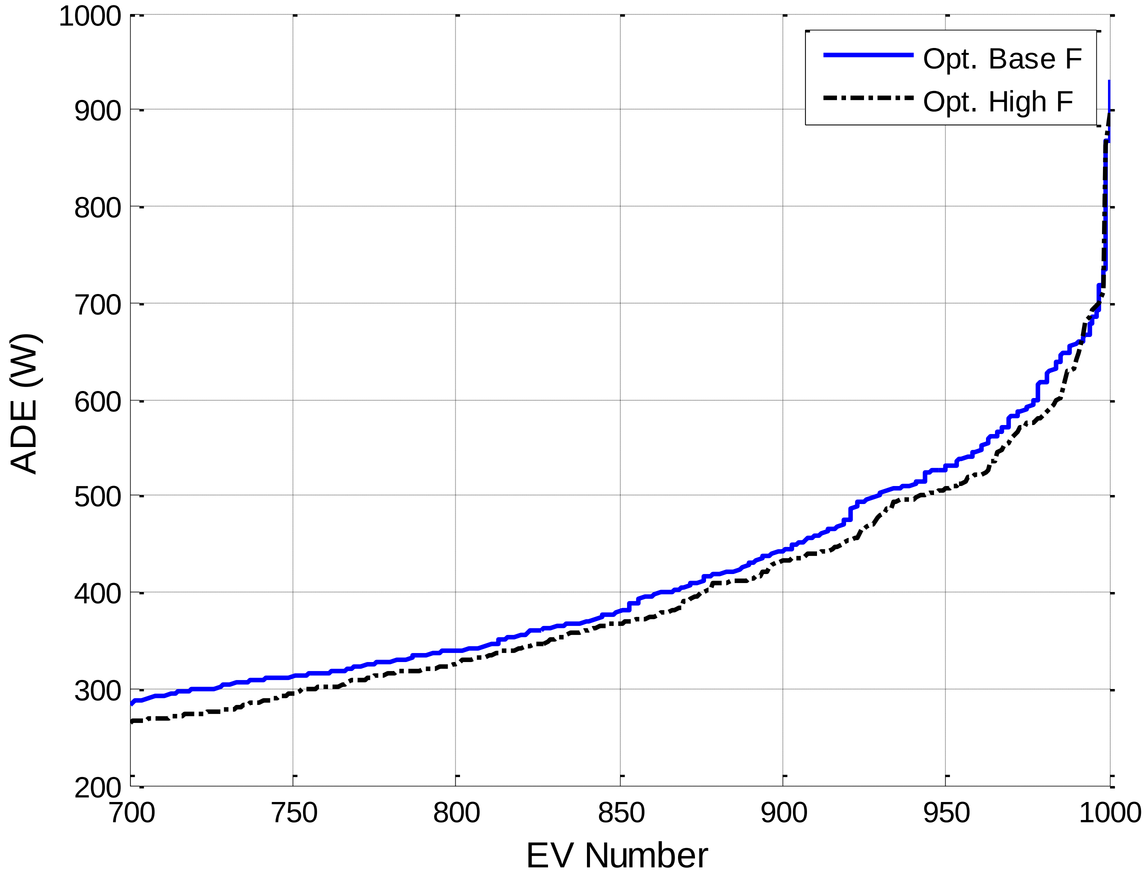

Figure 5. 25 Sensitivity Analysis on Mean ADE per EV using Optimal Model

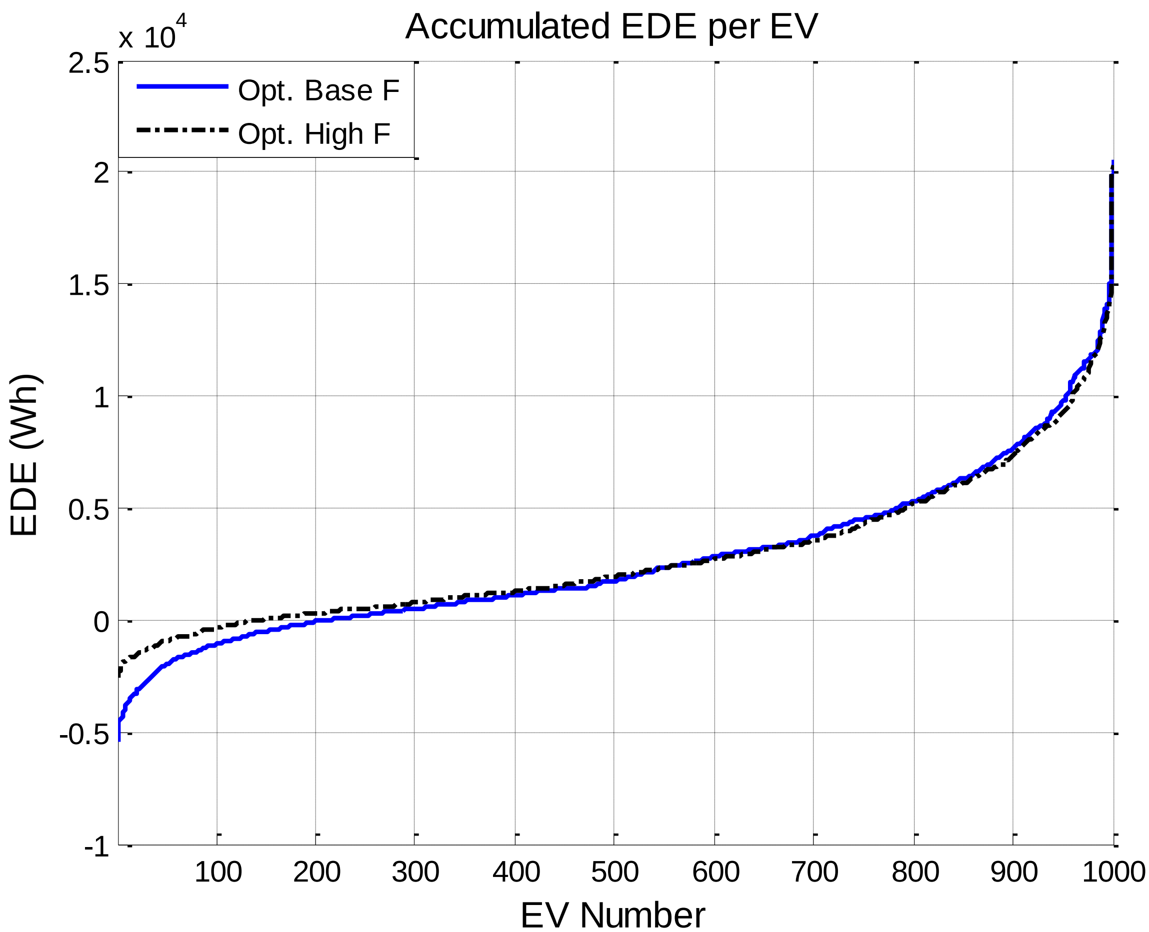

Figure 5. 26 Sensitivity Analysis on Total Accumulated EDE per EV using Optimal Model

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

A novel unidirectional dispatch algorithm for EVs performing discrete unidirectional regulation was developed in this work. It optimally switched EVs on and off to minimize the total number of communication messages sent to meet the system deployment signal while maintaining fairness in charging EVs with respect to the aggregator's overall schedule. Simulations on the PJM system showed that the required communications BW can be reduced by approximately 99.8% from incremental dispatch methods. The model was also compared to a benchmark heuristic model. While the BW reduction was about 3.2%, it was achieved while maintaining fairness in par with the benchmark model.

Sensitivity analysis was performed to evaluate the models' performance in response to receiving regulation signals higher than the scheduled values. It was shown that further significant improvements for up to about 22.6% can be obtained if a scheduling algorithm was updated in real-time with the aim of fully charging all vehicles. These reductions were achieved while maintaining high fairness in charging for the vast majority of the EV owners. Approximately 4.5% reductions in the absolute difference between actual and incremental dispatches were obtained using the optimal model as compared to the scaled signal. It can be concluded in general that optimal algorithm performed better than the previous state of the art one in all aspects. A sensitivity analysis was conducted which addressed varying the weight of fairness in the formulation. It was found out that more BW reductions can be achieved as F is decreased. This definitely comes on the expense of losing fairness in charging some of the vehicles.

Future work will focus on investigating the effects of using different maximum charger ratings and on extending the algorithm's advantages to EVs performing bidirectional V2G. Moreover, other formulations can be considered as variations of the developed ones.

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